Improving the understanding of poverty and social exclusion in Europe

EDITED BY ANNE-CATHERINE GUIO,
ERIC MARLIER AND BRIAN NOLAN

2021 edition

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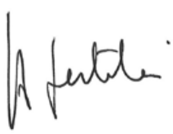
Foreword

Putting people first in Europe's post-COVID-19 recovery is at the heart of the European Pillar of Social Rights Action Plan, proposed by the European Commission in March 2021 and subsequently endorsed by the 27 European Union (EU) Member States. The backbone of this commitment is the EU target to reduce, during this decade, the number of people at risk of poverty or social exclusion by at least 15 million (including at least five million children), together with the EU targets on employment and on skills. The Recovery and Resilience Facility, the key instrument of 'NextGenerationEU', aims to help mitigate the socio-economic impact of the pandemic. It will help Member States make their economies and societies greener, more digital and more resilient.

Better understanding of poverty and social exclusion in Europe has become even more important in this context and is essential for close monitoring of Member States' progress towards the agreed EU targets. A more in-depth understanding is also needed to guide the necessary policy reforms and evaluate the effectiveness of the resources invested in achieving the ambitious objectives of the Action Plan. Crucial to all of this is the reliability of the available data and the development of accurate and robust indicators, such as those included in the scoreboard for the European Pillar for Social Rights. The quality of the analyses based on these data is also of key importance for understanding the complex and dynamic issues underlying poverty and social exclusion.

The Eurostat publication Improving the understanding of poverty and social exclusion in Europe provides in-depth analyses of the EU Statistics on Income and Living Conditions (EU-SILC). It aims to deepen our knowledge of the determinants and dynamics of income and living conditions, to suggest robust policy-relevant indicators and to examine the strengths and weaknesses of this dataset. It is the outcome of an EU-funded network of statisticians and social scientists who form a partnership that has extensive experience in the production and analysis of the EU-SILC data.

The present volume is intended not only for policy-makers, researchers and statisticians, but also, more broadly, for all those concerned with ensuring that economic and social progress in Europe go hand in hand.



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Economy, responsible for Eurostat

Commissioner Nicolas Schmit
Jobs and social rights

Acknowledgements by editors

The third Network for the Analysis of European Union Statistics on Income and Living Conditions (Net-SILC3) was an ambitious 17-partner Network (for a list of Net-SILC3 members, see Appendix 1) bringing together expertise from both data producers (directly involved in the collection of European Union (EU) Statistics on Income and Living Conditions (EU-SILC) data) and data users. It was established in response to a call for applications by the Statistical Office of the European Union (Eurostat) in 2016. We would like to thank Eurostat not only for funding Net-SILC3 but also for its active and efficient support throughout the project. This book and the companion Net-SILC3 book on *Improving the measurement of poverty and social exclusion in Europe: Reducing non-sampling errors* (edited by Peter Lynn and the late Lars Lyberg, who sadly passed away in March 2021) represent major outputs from Net-SILC3 and are successors to those produced by the first and second networks for the analysis of EUSILC (Net-SILC1 and Net-SILC2 [1]).

We wish to thank all the Net-SILC3 members and the institutions they belong to for their contribution to the project. The initial Net-SILC3 findings were presented at the first international conference on Comparative EU Statistics on Income and Living Conditions (in Athens, 19–20 April 2018). The second international conference, planned to take place in Rome in May 2020, had unfortunately to be cancelled because of the first COVID-19 lockdown. We would like to thank the Hellenic Statistical Authority (ELSTAT) for kindly hosting the first conference and the Italian National Statistical Institute (ISTAT) for having kindly agreed to host the second one.

In addition to these two conferences, four methodological 'best practice workshops' were organised as part of Net-SILC3.

- The first workshop, on 'Assessing and improving the validity and comparability of the EU-SILC income, own consumption, health and housing variables', took place in Athens in April 2018. This event was hosted by ELSTAT and organised jointly by the Luxembourg Institute of Socio-Economic Research (LISER) and the University of Antwerp.
- The second and third workshops, both on 'Frame errors and non-response, weighting and calibration and imputation for income variables', took place in Colchester (United Kingdom) in February 2019. It was kindly hosted by the Institute for Social and Economic Research (ISER), University of Essex, and organised by LISER together with ISER.
- The fourth workshop, on 'Impact of different modes of data collection', was ready to take place in Rome in May 2020 but had to be cancelled because of the first lockdown.

We want to thank Isabelle Bouvy and Begoña Levices for invaluable secretarial and bibliographical help.

We want to stress that the book does not represent in any way the views of the European Commission or the European Union. It also does not represent in any way the views of the persons and bodies thanked above. All the authors have written in a strictly personal capacity, not as representatives of any government or body. Thus, they have been free to express their own views and to take full responsibility for the judgements made about past and current policy and for the recommendations for future policy.

Finally, we want to recognise once again the central contribution made by Tony Atkinson to Net-SILC1 and 2, which have served to inspire Net-SILC3.

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[1] The Net-SILC1 book on *Income and Living Conditions in Europe* (eds A. B. Atkinson and E. Marlier) is available free of charge (https://ec.europa.eu/eurostat/documents/3217494/5722557/KS-31-10-555-EN.PDF) and the Net-SILC2 book on *Monitoring Social Inclusion in Europe* (eds A. B. Atkinson, A.-C. Guio and E. Marlier) can be downloaded (http://ec.europa.eu/eurostat/documents/3217494/8031566/KS-05-14-075-EN-N.pdf/c3a33007-6cf2-4d86-9b9e-d39fd3e5420c).

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1 Improving the understanding of poverty and social exclusion in Europe

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1.1. Aims of Net-SILC3 and policy context of the book

1.1.1. Aims of Net-SILC3

The aim of Net-SILC3 was to carry out in-depth methodological work and socioeconomic analysis of the EU-SILC data (covering both cross-sectional and longitudinal dimensions), and develop common tools and approaches regarding various aspects of data production for the whole European Statistical System.

The plans for the network built on a solid foundation of previous work (especially in the context of Net-SILC1 and 2) and sought to address various methodological and analytical questions that were of particular importance at this stage of the maturation of EU-SILC.

The 26 Net-SILC3 research work packages were organised around two thematic clusters.

The first cluster covered the issue of non-sampling errors in the context of EU-SILC. It was designed to identify the main sources of non-sampling errors in the instrument, to describe the nature and impact of each type of error, and to produce guidance on reducing them. The result of this cluster is published in a second book: *Improving the measurement of poverty and social exclusion in Europe: Reducing non-sampling errors* edited by Peter Lynn and Lars Lyberg (2021).

The second cluster, which is the subject of this book, aimed to deepen our knowledge of the determinants and dynamics of income and living conditions through in-depth analyses of a variety of socioeconomic issues. Another key objective of this cluster was to suggest robust policy-relevant indicators in this field, including longitudinal indicators. The aim of this book is to bring together the findings of the research effort this entailed, involving many different researchers and covering a very wide range of topics. The book is organised as follows:

- the book, its policy context and the EU-SILC instrument (Chapters 1 and 2);
- improving the understanding of inequalities (Chapters 3–6);
- evaluating the role of social transfers and how best to measure poverty (Chapters 7–9);
- inequalities in health and housing conditions (Chapters 10–12);
- deprivation of children and among couples (Chapters 13 and 14);
- the dynamics of poverty and social exclusion (Chapters 15 and 16);
- methodological and conceptual issues linked to the design and coverage of EU-SILC (Chapters 17–20).

1.1.2. Policy context

It is important to make clear at the outset that the research on which this book reports and draws was carried out before the onset of the coronavirus disease 2019 (COVID-19) pandemic. This pandemic has been a profound economic and social global shock, with impacts on and implications for economic and social policies that will be with us for many years. This has major implications for, inter alia, social monitoring in the future, which will clearly require in-depth consideration, as touched on at the end of this chapter. Notwithstanding that pressing need, we trust that this book, reflecting the results of almost 5 years of research, will be an important contribution to the development of EU-SILC and the EU social indicators. We also hope that it will contribute to the wider appreciation of the uses that can be made of EU-SILC data and to the strengthening of the social dimension of the European Union.

Most of the Net-SILC3 research was carried out during the second half of the Europe 2020 strategy on smart, sustainable and inclusive growth, upon which EU Heads of State or Government agreed in 2010. This strategy included five headline targets, including a poverty and social exclusion target: to reduce by at least 20 million the number of people at risk of poverty or social exclusion (AROPE ([2])) in the EU as a whole between 2010 and 2020. The EU AROPE indicator is an aggregate indicator, which consists of three indicators:

1. the EU at risk of poverty (AROP) indicator, which identifies people living in a household with a total equivalised disposable income below a threshold set in each country at 60 % of the national median equivalised disposable income (see Chapter 2 for detailed information on income measurement);
2. the EU severe material deprivation (SMD) indicator, which identifies people living in a household who cannot afford at least four out of a list of nine items ([3]);
3. the EU (quasi-)joblessness (QJ) indicator, which identifies people (0–59 years) who live in a household with very low work intensity, that is, where the adults (those aged 18–59, but excluding students aged 18–24) worked less than 20 % of their total combined work-time potential during the previous 12 months.

At the time of finalising this book, that is, the end of the Europe 2020 strategy, we have to recognise that progress towards this important target was clearly not as great as expected: in concrete terms, the target was that the number of AROPE people should be reduced from 116.1 million (estimated on the basis of 2008 EU-SILC data, the most recent data available when the target was adopted in 2010) to 96.1 million (to be computed on the basis of 2018 EU-SILC data). However, as shown in Figure 1.1, the 2018 EU-SILC figure is considerably higher than this objective: 109.9 million. It should be highlighted that, even if this number has decreased to 107.5 million people in 2019, it is still more than 11 million higher than the target.

In 2019, the Employment Committee and the Social Protection Committee (SPC) of the Employment, Social Policy, Health and Consumer Affairs Council configuration jointly produced a very useful assessment of the Europe 2020 strategy, which includes a reflection on the importance of target setting in the social and employment areas. One of their key conclusions is that (European Commission, 2019, p. 7):

'There is strong support among the Committees' members that the use of targets in general has proved to be useful in driving forward ambitious policy reform, but some concerns are raised that the headline targets are not assessed in a sufficiently integrated manner. It is emphasised that setting employment and poverty and social exclusion targets have certainly fed and informed policy debate at EU and national levels and helped increase the visibility of the employment and social policy strands.

'The targets and associated indicators in the fields of employment and of poverty and social exclusion are generally felt to serve as an effective tool for monitoring the progress achieved against the employment and social objectives of Europe 2020,

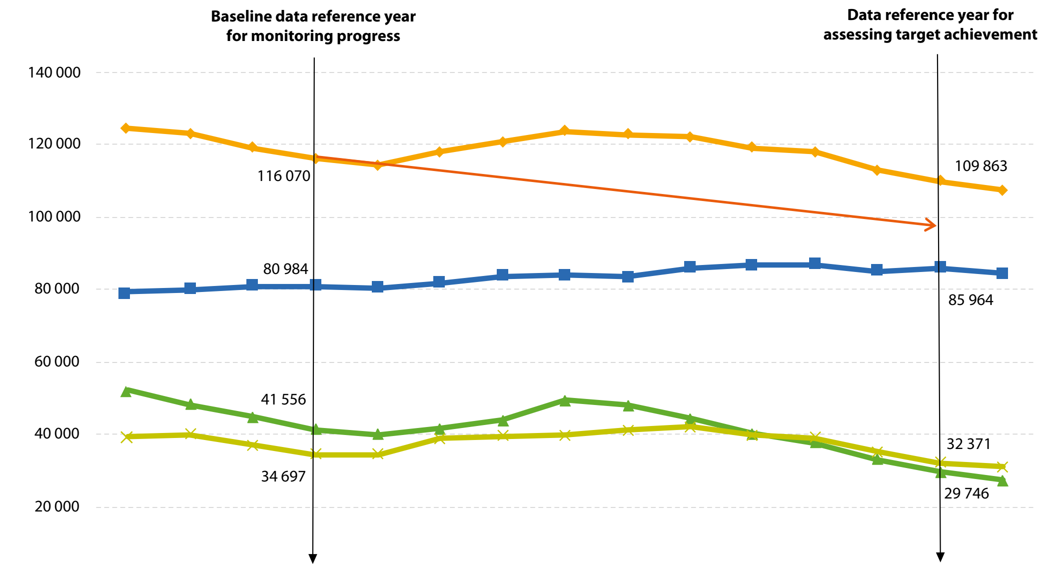
([2]) See Appendix 2 for a list of acronyms.
([3]) The nine items are: 1) people in these households cannot face unexpected expenses; 2) they cannot afford one week annual holiday away from home; 3) they cannot avoid arrears (in mortgage or rent, utility bills or hire purchase instalments); 4) they cannot afford a meal with meat, chicken, fish or a vegetarian equivalent every second day; 5) they cannot keep their home adequately warm; 6) they do not have access to a car/van for private use if needed; 7) they cannot afford a washing machine; (8) they cannot afford a colour television and 9) they cannot afford a telephone People are materially deprived if they live in a household that lacks at least three of these nine items. If the household lacks four or more items, the person is severely materially deprived.

with the quality of the indicators used for monitoring seen as being sufficient for purpose. There is also strong support to the view that the setting of national targets (in addition to an overall, common target) has been useful for supporting national policy reforms.'

Is it time to give a new push to a social target 10 years later? We think it is, and therefore welcome the fact that in its proposal for a European Pillar of Social Rights action plan, released on 4 March 2021, the European Commission suggests that the EU should be committed to reducing the number of AROPE people by at least 15 million (including at least 5 million children) by 2030 (European Commission, 2021). Such a target is even more important in the context of the COVID-19 pandemic, which is expected to worsen the social situation in EU Member States.

The next section (Section 1.2) provides a short description of each chapter, so that the reader can obtain an impression of their contents. Section 1.3 then considers some of the key issues raised by the Net-SILC3 researchers for the future development of EU-SILC and of EU social indicators. Finally, Section 1.4 briefly notes the implications of the COVID-19 pandemic for future social monitoring, discussed in Chapter 20.

Figure 1.1: Progress towards the EU social inclusion target, EU-27, 2008–2020
(in thousands)



	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
AROPE	124 656	122 936	119 205	116 070	114 390	117 907	120 858	123 774	122 852	122 063	119 077	118 056	112 917	109 863	107 535
AROP	79 498	80 159	80 989	80 984	80 573	82 020	83 856	84 024	83 419	85 991	86 760	86 908	85 209	85 964	84 520
SMD	52 254	48 283	44 834	41 556	40 137	41 682	44 003	49 496	48 079	44 509	40 414	37 804	33 137	29 746	27 491
QJ hhds	39 520	40 051	37 114	34 697	34 699	38 978	39 675	39 863	41 148	42 138	39 822	39 145	35 377	32 371	31 255

Reading note: In 2008, the reference (survey) year for the Europe 2020 poverty and social exclusion target agreed upon in 2010, 80.984 million people were at risk of poverty (AROP), 41 556 million were severely materially deprived (SMD) and 34 697 million lived in (quasi-)jobless households (QJ). The sum of these three figures is higher than the number of people who were at risk of poverty or social exclusion that year (AROPE, 116 070 million) because a number of AROPE persons combine two or even all three difficulties considered in this aggregate indicator.

Source: Eurostat, EUSILC (codes t2020_50, t2020_51, t2020_52, t2020_53), downloaded on 4 March 2021.

1.2. Outline of the book

The book opens with a description of the key statistical instrument used in this book: EU-SILC. In Chapter 2, Emilio Di Meglio, Didier Dupré and Sigita Grundiza describe how EU-SILC was implemented up until 2020 (for post-2020 EU-SILC, see Chapter 20). Every year in Europe around 300 000 households and more than 600 000 individuals are interviewed and the microdata are sent to Eurostat. EU-SILC has a legal basis, which is binding on EU Member States, and it is based on a common 'framework' that consists of common procedures, concepts and classifications, including a harmonised list of target variables to be transmitted to Eurostat. EU-SILC has a cross-sectional component pertaining to a given time period and a longitudinal component allowing it to measure changes at individual person/household level over a 4-year period. It is a multidimensional instrument covering income, housing, labour, health, demography, education and deprivation. EU-SILC has become the key EU reference for data on poverty, income distribution and living conditions. Chapter 2 describes in detail the income concept used in EU-SILC (i.e. the various income components included in the total household income and the income reference period) and explains how the concept of equivalised disposable income is computed on the basis of the so-called *OECD-modified (equivalence) scale*.

Chapter 3, 4, 5 and 6 aim to improve our understanding of inequalities.

In Chapter 3, Stefano Filauro and Alessia Fulvimari analyse how the inequality contributions of different income sources developed in two specific periods: the crisis years (2008–2013) and the subsequent recovery (2013–2008). To do so, they carry out an inequality decomposition by income sources, and present evidence for the overall changes of the inequality contributions of market income sources, social transfers and taxes. They find that during the crisis years labour income shares fell in a number of countries but they slightly increased in the subsequent recovery. In turn, as the development of shares and inequality contributions is highly correlated, the disequalising role of labour income declined in the first period and subsequently slightly increased in the recovery period on average across the EU. These trends were the result of different, but at times reinforcing dynamics of earnings and self-employment income. The disequalising role of capital income has declined in countries where it has a large share and where it was possible to use reliable data derived from registers. The equalising role of taxes has somewhat reduced in a majority of EU countries over these periods. However, all in all, there are markedly heterogeneous trends in the inequality contributions of the different market and welfare sources across the EU. The authors also highlight the current limitations of this exercise. Indeed, they could only analyse within-country changes of the inequality contributions, as this requires fewer assumptions about data reliability than comparing the levels of the inequality contributions between countries. Varying reliability of capital income and the difficulty of deriving earnings net of social contributions prevent them from carrying out a comparison of shares and inequality contributions for the different income sources between countries.

Chapter 4, written by Matthias Till, addresses the measurement of spatial disparities in the EU. It applies an algorithm to enhance the precision of regional estimates in EU-SILC by averaging estimates over three consecutive years. The AROPE indicator is presented for 126 areas defined by urban and non-urban Nomenclature of Territorial Units for Statistics (NUTS) regions in six countries. Standard errors indicate a precision gain of approximately 25 % compared with single-year estimates. For 70 regions, the standard error of AROPE remains below 2.5 percentage points. A regional quintile ratio is presented as an overall measure of disparity. The results confirm a particularly high degree of spatial disparity in Italy, where its poorest regions have an AROPE rate 2.4 times the magnitude of those in the poor regions in the south of the country. Several regions in which AROPE changed significantly between 2008 and 2018 are revealed.

Chapter 5 focuses on inequalities between foreign-born households and the rest of the population. Alessio Fusco, Rhea Ravenna Sohst and Philippe Van Kerm provide new evidence about the relative differences in the income and living conditions of native- and foreign-born families, exploiting EU-SILC data for 2007 and 2018. For the 28 countries that collect EU-SILC data with satisfactory coverage of immigrant populations, they document where the foreign-born stand along the distribution of incomes and living conditions and then derive their contribution to seven social indicators. They find that individuals living in foreign-born households have lower incomes and higher levels of poverty and deprivation in all countries examined. No clear improvement in the relative position of foreign-born households was observed between 2007 and 2018. Although there is much heterogeneity in the incomes of foreign-born households, their generally disadvantaged situation implies that, on the whole, they push inequality, poverty and deprivation indicators upwards. This effect persists in many countries, albeit mitigated in magnitude when the authors account for the different characteristics of foreign-born people compared with natives.

In Chapter 6, Elena Bárcena-Martín, Francisca García-Pardo and Salvador Pérez-Moreno rely on a fuzzy approach to the measurement of the 'leaving no one behind' principle underlying the United Nations' Sustainable Development Goals (SDGs ([4])). Taking the AROPE framework as reference, they provide country-level measures for 2017 of the extent to which individuals are left behind in terms of multidimensional poverty, and changes in them compared with 2013. They conclude that people tend to be left behind to a greater extent in the income dimension, followed by work intensity, and to a lesser extent in material deprivation. From a time perspective, their results reveal that over the post-crisis period, 2013–2017, despite considerable variations across countries, 15 out of the 28 EU-SILC countries they analyse significantly reduced the degree to which people are left behind, and the people most left behind benefited proportionately more from economic prosperity. Finally, they identify the risk factors of being left behind and show that the most prominent features of those left behind include having a chronic illness, living in a single-parent household and being 60 or over. Immigrants, women and younger individuals are also prevalent among those most left behind.

([4]) See: https://sdgs.un.org/goals

The following three chapters (7–9) aim to improve our understanding of the role of social transfers and how best to measure income poverty.

The aim of Chapter 7, written by Chrysa Leventi, Andrea Papini and Holly Sutherland, is to explore alternative ways to define social transfers and measure their effects on income poverty reduction in the EU-27. Using microsimulation techniques, they attempt to analyse the effects of treating social benefits and pensions in net or gross terms, the role of different types of benefits and the impact of policy interdependencies when constructing hypothetical scenarios in which some transfers are set to zero. They find that the average contribution of net transfers to income poverty reduction is smaller than the corresponding contribution of gross transfers. Depending on whether transfers are considered gross or net, the ranking of countries also changes substantially in terms of the anti-poverty effectiveness of their monetary social provision systems. Non-means-tested benefits seem to explain most of the total impact of benefits on income poverty reduction.

Chapter 8, by Geranda Notten and Anne-Catherine Guio, complements established methods that use income to evaluate effectiveness of social transfers, by estimating the effects of these transfers on the new indicator of material and social deprivation (MSD) ([5]) adopted by the SPC and its indicators subgroup in 2017. It shows that the impact on deprivation of a universal annual EUR 150 social transfer (expressed in purchasing power standards (PPS) ([6])) is higher among persons who have fewer resourc-

([5]) The EU MSD indicator consists of 13 items. Seven items relate to the person's household: these are items 1–6 included in the material deprivation indicator presented above plus the inability of the household to replace worn-out furniture. Six items relate to the individuals themselves: the inability of the person to (1) replace worn-out clothes with new ones; (2) have two pairs of properly fitting shoes; (3) spend a small amount of money each week on oneself ('pocket money'); (4) have regular leisure activities; (5) get together with friends/family for a drink/meal at least once a month; and (6) have an internet connection. A person lacking (enforced lack) at least 5 of these 13 items is materially and socially deprived; if they lack 7 or more items, the person is severely materially and socially deprived. For more technical information on the former 'material deprivation' indicator and on the more recent MSD indicator, see https://ec.europa.eu/social/main.jsp?catId=818&langId=en&id=82.

([6]) On the basis of purchasing power parity (PPP), PPS convert the amounts expressed in a national currency to an artificial common currency that equalises the purchasing power of different national currencies.

es, an effect that is present both within and across countries and underlines the importance of a progressive social transfer system. From an econometric point of view, this chapter offers new methodological insights, by systematically comparing the performance of count data models (Poisson, negative binomial and zero-inflated negative binomial) and ordered regression models (ordered logit and generalised ordered logit) to predict the deprivation distribution. It finds that ordered logit models systematically outperform the count models.

In Chapter 9, Rolf Aaberge, Andrea Brandolini and Iryna Kyzyma aim to reconsider poverty measurement and the associated anti-poverty allocation in Europe by highlighting the limitations of headcount measures of poverty. The chapter addresses the two features of headcount measures – the arbitrariness of the choice of the threshold and the insensitivity to the severity of poverty – by considering two groups of threshold-free poverty measures. One group of measures focuses on the number of poor people and is a weighted average of headcount ratios, whereas the other group focuses on how poor the poor people are and is a weighted average of relative poverty gaps. Their results suggest that the correlation of country rankings based on the different selected measures is high and statistically significant. However, accounting for income distribution below the poverty threshold impinges on the evaluation of poverty levels: the extent to which measured poverty is higher in one country than in another depends heavily on the choice of the poverty index. Furthermore, depending on the poverty index chosen, the optimal allocation of an anti-poverty budget may change considerably, prioritising the richest or the poorest among the poor.

In Chapters 10 to 12, we leave the income and material deprivation dimensions to investigate inequalities in health and housing conditions.

Chapter 10 investigates if risk adjustment affects cross-country comparisons of unmet medical need. Valerie Moran, Andrea Riganti, Luigi Siciliani and Andrew Jones argue that adjusting unmet need for factors that lie outside the health system can improve the comparability of health system performance in the healthcare access domain. The authors use logit models to explore (1) if differences in unmet need are quantitatively and statistically significant across countries; and (2) the extent to which differences remain after adjusting for demographic (age and gender), health (chronic conditions, self-reported general health and limitations in activities due to health problems) and socioeconomic (education, AROP, unemployment and income) variables. Their results indicate that differences in unmet need reduce only by a small extent after controlling for demographic, health, education, AROP and unemployment variables, but are more marked after controlling for income.

In Chapter 11, Johannes Klotz, Matthias Till and Tobias Göllner assess excess mortality in the Europe 2020 AROPE target group. Cross-sectional EU-SILC observations from five countries (Belgium, Bulgaria, Spain, Latvia and Austria) were pooled over several survey years and then merged with death records from national mortality registers in follow-up periods. Their data set contains more than 180 000 individuals aged 30–79 years at baseline, of whom more than 10 000 died. Excess mortality is estimated by Cox regression proportional hazard ratios, controlling for age and sex. The average hazard ratio (AROPE vs non-AROPE) across the five countries is 1.69 for males and 1.44 for females, implying a life expectancy disadvantage of 6 years among men and 4 years among women. Despite huge variation in the AROPE prevalence, excess mortality is rather similar between countries. Hazard ratios are amplified at working ages and among the 'intersection' subgroup, which meets at least two out of the three AROPE criteria.

Chapter 12, by Ida Borg and Anne-Catherine Guio, studies the variations between EU countries in a large range of housing problems and examines to what extent these between-country differences can be explained by measurable factors, at micro or macro level. In terms of micro drivers, the results confirm the impact of risk factors related to the household's resources and costs/needs. They also indicate that most of the risk factors have a similar impact on all the dimensions of housing, with some variation due to the position in the life cycle. However, for the EU indicator of housing cost overburden (based on the share of housing cost in disposable income), some results go in the opposite direction from the subjective housing cost overburden and to the other housing problems analysed. This indicates that further investigations regarding the construction and the reliability of this EU indicator are needed. In terms of macro drivers, the results confirm that historical and institutional factors affect the availability and quality of housing. The results also indicate that in-kind transfers and the level of national affluence have a protective impact on housing deprivation, even when household-level determinants (such as household income) are taken into account.

Chapters 13 and 14 focus on material deprivation.

Chapter 13 combines single-level and multilevel models to get a full picture of child deprivation drivers in EU countries, using the 17 items included in the EU chid-specific indicator adopted by the SPC and its indicators subgroup in 2018 to measure child-specific deprivation at EU level. In this chapter, Anne-Catherine Guio, Eric Marlier, Frank Vandenbroucke and Pim Verbunt analyse the combined impact that variables related to the long-term command over resources and variables indicating household needs have on the risk of child deprivation. Their results show that the relationship of these variables with child deprivation differs across countries. In the richest countries, the explanatory power of the variables related to household needs is the largest, whereas, in the most deprived countries, the explanatory power of resource variables is generally greater. They also find a significant relationship between gross domestic product (GDP) per capita and child deprivation, even when individual household incomes are included. This is not self-evident, as it shows that GDP per capita is a proxy for important contextual variables that are not reflected in individual incomes and other individual characteristics.

Chapter 14 highlights the value of opening the 'black box' of intra-household distribution, looking at differences in deprivation within couples. Anne-Catherine Guio and Karel Van den Bosch show that, in a large majority of couples, no imbalance in deprivation is apparent, mainly because neither partner lacks any item. However, when focusing on those couples in which at least one item is lacked by one partner, the proportion of 'diverging couples' is substantial. Furthermore, even if the percentage in which the woman is the disadvantaged partner is close to the proportion of couples in which the man is in this situation, there is clear evidence that the intra-couple gender deprivation gap is systematically biased to the disadvantage of women. The authors show that the work status of the partners and their share of joint income are important determinants of the intra-couple gender deprivation gap. The results of the multivariate analysis also suggest that national differences were not fully explained by the model and may be due to idiosyncratic factors. The authors argue for a range of adaptations in the data collection, as the quality of the data is crucial to present a correct picture of the gender deprivation gap within couples at EU level.

The next two chapters investigate the dynamics of poverty.

Chapter 15 investigates the dynamics of in-work poverty and in-work MSD, that is, the extent of workers' mobility into and out of in-work poverty and in-work deprivation. In this chapter, Anne-Catherine Guio, David Marguerit and Ioana Cristina Salagean investigate to what extent the trajectories into and out of in-work poverty/deprivation can be explained by individual factors, household characteristics and trigger events. They highlight the different trajectories: more than half of the working poor/deprived remain working poor/deprived in the second year, although more than one third keep on working and manage to escape poverty/deprivation; and 5 % stop working and remain in poverty. They also show that, of the non-working poor who find a job in the second year, half do not manage to escape poverty and become working poor.

In Chapter 16, Sabina Alkire and Mauricio Apablaza (with Anne-Catherine Guio) contribute to the understanding of chronic multidimensional poverty in the EU. Using EU-SILC longitudinal data, they construct two types of indicators to explore multidimensional poverty dynamics and chronicity. The first indicator mimics the AROPE indicator and is based on its three dimensions. The second indicator is an extended measure that includes other salient dimensions of social exclusion: education, health and housing. The numerous charts and tables provided in this chapter illustrate in a simple way the toolkit available when using chronic multidimensional poverty indexes in an international context. The choice of dimensions and cut-off remains to be made at EU level, but the toolkit can easily be used to provide, for each EU country, a multidimensional poverty rate, together with the duration, intensity and dynamics of multidimensional poverty.

Finally, the last four chapters (17–20) address methodological and conceptual issues linked to the design and coverage of the EU-SILC instrument.

As EU-SILC relies on a four-wave rotational panel design, a new population sample is drawn every year and selected respondents are interviewed annually for up to 4 years. This means that a complete EU-SILC cross-sectional data set contains data from samples drawn independently in 4 different years. In Chapter 17, Alessio Fusco, Giovanni Gallo and Philippe Van Kerm apply influence function (IF) regression methods to examine to what extent this design has an impact on the estimates of four EU social indicators (the AROPE AROP indicators, the MSD indicators, introduced above, and the Gini coefficient ([7])), in other words if a rotation group bias in these indicators is observed. Their analysis highlights that estimates of income inequality and poverty rates for newer rotation groups are often higher than for older ones. Individuals interviewed at least twice (and especially those who have been in the sample for 3 or more years) tend to drag the selected social indicators downwards, compared with individuals interviewed for the first time. These impacts remain significant even when accounting for observable sociodemographic characteristics of households; not all countries are affected by the bias, however.

In Chapter 18, Tim Goedemé, Marii Paskov and Brian Nolan discuss the potential of using the European Socio-economic Classification (ESeC) in EU-SILC. They consider all countries and years available from EU-SILC (between 2004 and 2018) and illustrate some of the data limitations by looking into levels of and trends in in-work poverty by social class. They show that the main challenges for reconstructing ESeC in EU-SILC include the limited and varying level of detail of the occupational variable (International Standard Classification of Occupations (ISCO)), the change from ISCO-88 to ISCO-08 in EU-SILC 2011 and the varying availability of key variables, in particular for the self-employed and the unemployed. In countries with the single-respondent model, information on the non-selected respondents is also limited. This chapter shows that, in all countries, poverty risks vary considerably by social class. However, while data concerns should be taken seriously when studying trends or cross-country differences, EU-SILC presents an opportunity for informative comparative studies on social class inequality.

Veli-Matti Törmälehto then investigates in Chapter 19 the coherence between the EU-SILC income aggregates and those provided by national accounts. He discusses factors that could influence the observed discrepancies, and adjusts for the main conceptual differences. In line with other studies, he finds that the micro/macro gaps vary significantly across countries, and are more substantial in property and self-employment income than in wages and salaries and in transfers received. He also examines the sensitivity of key social indicators to the micro/macro discrepancies by adjusting the microdata totals to match the reconciled macro aggregates. He tests three adjustment methods (simple proportional scaling, calibration to margins and Pareto imputation), and compares their impact on the measures of income inequality and AROP. Adjusting the microdata to the gaps results in significant increases in inequality and median income levels, but more subdued changes in AROP rates. The results are sensitive to the adjustment methods and in particular to the proper assessment of the micro/macro gaps.

Finally, Chapter 20, by Estefanía Alaminos, Emilio Di Meglio, Didier Dupré, Sigita Grundiza and Agata Kaczmarek-Firth, complements Chapter 2 by describing the developments carried out in the framework of the modernisation of social statistics at EU level, especially regarding the revision and improvement made to EU-SILC, as well as the new legislation regarding its implementation with effect from 2021. The chapter presents the integrated European social statistics (IESS) regulation: Reg-

([7]) The Gini coefficient is an income inequality indicator based on the cumulative share of income accounted for by the cumulative percentages of the number of individuals, with values ranging from 0 (complete equality) to 1 (complete inequality, i.e. one person has all the income, all others have none).

ulation (EU) 2019/1700 of the European Parliament and the Council ([8]), which establishes a common framework for European statistics related to persons and households, based on data at individual level collected from samples. This regulation was adopted in October 2019 and the underlying implementing acts pursuant to the IESS regulation were then adopted in December 2019.

1.3. Further development of EU-SILC and EU social monitoring

Throughout this book, like its two predecessor volumes (Atkinson and Marlier, 2010; Atkinson, Guio and Marlier, 2017), a core focus has been on how best to fully exploit the potential of EU-SILC to enhance the understanding of core social outcomes and relationships, and contribute to guiding policies. The range of topics covered in the book and the geographic scope of the analyses across so many countries serve to underline how much has been achieved and also point to further advances. In terms of achievements, the book confirms what had already been highlighted by Atkinson, Guio and Marlier (2017, p. 41): 'EU-SILC is a remarkably successful statistical instrument. It provides an essential input into the policymaking process. Without such a rich source of data, the EU would not have been able to set a quantified social inclusion target as part of the Europe 2020 strategy, nor to develop an evidence-based 'Beyond GDP' initiative. The whole EU social indicators process would have been impossible without this investment in statistics.'

Drawing on the various chapters of the present volume, we suggest in this section a variety of topics that could be fruitfully pursued, and also what would assist in doing so in terms of further development of the instrument and its use. We then conclude, in Section 1.4, by noting some immediate and longer-term implications of the COVID-19 crisis.

([8]) https://eur-lex.europa.eu/eli/reg/2019/1700/oj

1.3.1. Improving the understanding of income distribution on a comparable basis

An overarching challenge to be noted at the outset is the need to further enhance the accuracy, reliability and comparability of data, especially those underlying core monetary indicators. Indeed, the quality of EU social indicators measuring income poverty and inequality relies heavily on the quality of the underlying income data from which they are calculated. In that context, the increasing use of information on earnings and social transfers from administrative sources in measuring household incomes across various countries is very welcome in improving accuracy and reliability; at the same time, the differences in the extent of use of administrative data can affect the comparability of income-based indicators both across countries and over time. To cite just one example, Chapter 3 points out that it hinders the comparison between countries in terms of inequality decomposition by income source, because some sources are more likely to be under-reported in countries that do not use administrative sources than in countries that do. This result is also (generally) found in Chapter 19, which investigates the gaps between EU-SILC and national accounts income aggregates. This chapter also shows that the coverage rates for self-employment and property income remain low in many countries, and that more work is needed on the concept and measurement of these income sources, including methods to impute or model property income based on asset values or external information. The central recommendation of Chapter 19 is that any adjustments to the microdata should be done with a microsimulation model, properly accounting for what is deemed to be correction of measurement error and what is imputation to attain consistency with macro aggregates. Drawing distributional conclusions from macro-adjusted microdata should also be accompanied with accessible sensitivity analysis and full transparency with regard to data sources and methods.

Tracking the impact of data-gathering practices on measured incomes, both in a given country over time and across countries at a point in time, is extremely important. The new detailed typology to document breaks in series, which will be used in the revised, post-2020 EU-SILC and will make users more aware of the nature and extent of the breaks, is therefore very welcome. As far as changes implemented in the future are concerned, as suggested in Chapter 18, it would also be extremely useful in the event of changes to the mode of data collection, and changes in weighting schemes, if key variables could be made available on an 'old' and 'new' basis so the impact of changes could be seen by users.

1.3.2. Improving the understanding of intra-household and intergenerational differences in deprivation

Alongside income, material deprivation indicators have been extremely useful in the monitoring of living standards across the EU, especially during the 2008 economic and financial crisis, and in the monitoring of the Europe 2020 strategy throughout the last decade.

As mentioned above, considerable progress has been made in the measurement of deprivation over the last few years, with the adoption at EU level of the MSD indicator (in 2017) and of the child-specific deprivation indicator (in 2018). It is encouraging that in early 2021 the SPC and its indicators subgroup agreed on a revised definition of the AROPE indicator in which the SMD indicator is replaced by the more robust indicator on severe MSD (see definition above) (9).

The new MSD indicator offers an important window into differences in deprivation levels within the household, which can be further developed, as Chapter 14 highlights. It could also be further used to better understand intra-household differences between generations. Chapter 14 discusses some necessary improvements in the way adult deprivation items are collected. The use of proxy interviews for collecting the MSD items may have an impact on the deprivation reported. It is therefore very welcome that, from 2021, the revised EU-SILC will limit the use of proxies for deprivation data, as is already done for other sensitive adult EU-SILC questions related to education, well-being or health. In some countries (Denmark, the Netherlands, Finland and Sweden), the study of intra-household differences is unfortunately impossible at the moment, because individual data on deprivation are only collected for the selected respondent – so differences between individuals within the household cannot be investigated at all. While the pragmatic reasons for adopting this strategy are clear, the implications merit further consideration in future, for the measurement of deprivation at individual level and for the analysis of intra-household deprivation.

Chapter 13 shows the value of using the new child-specific indicator to analyse the living conditions of children, which may differ from those of their parents. One limitation of the children's items collected in EU-SILC is, however, stressed by the authors: the information sought is if at least one child in a household does not have an item, and that is taken to apply to all the children in that household. It would be preferable to seek to capture the deprivation level of each child in a household, allowing differences between, for example, girls and boys or teenagers and younger children to be assessed.

1.3.3. Improving the understanding of the situation of those left behind

Evaluating the extent to which people are left behind, and better identifying who those people are, are essential in the monitoring of social policies. Chapter 6 allows progress in this direction by presenting a measure based on the AROP, SMD and QJ indicators to evaluate how much each specific individual is left behind in these dimensions.

Similarly, the threshold-free distributionally sensitive measures proposed in Chapter 9 provide a valuable robust complement to the current income-based social indicators currently produced from EU-SILC.

(9) It should be noted that the QJ indicator included in the AROPE indicator has also been amended. It is now extended to the population aged 0–64 (instead of 0–59) and fine-tuned in order to ensure an appropriate selection of the adult (18–64) population taken into account in the measurement of the work intensity of the household.

Another element of the need to improve knowledge of the circumstances and living conditions of those left behind relates to specific groups that are difficult to incorporate and distinguish adequately in general surveys such as EU-SILC, for a variety of reasons. A prominent example is provided in Chapter 5, which highlights the importance of investigating the (disadvantaged) position of foreign-born households compared with native ones. The heterogeneity of the foreign-born group should, however, be recognised and is currently obscured by the fact that the country of origin is not provided in the EU-SILC User Database (UDB). The UDB only distinguishes between immigrants born in another EU country and those born outside the EU. In future, providing users with the exact country of birth would be of considerable analytical value. The coverage of this group is also extremely challenging. The most vulnerable immigrant groups may be missing in EU-SILC. Recent migrants may not yet be included in survey sampling frames, the most vulnerable may be living in reception centres and communal living arrangements rather than private households, some of those in private households may change accommodations very frequently, and low response rates may reflect language or cultural barriers, uncertainty about legal status, or lack of trust. We should also keep in mind that information on the country of birth is recorded according to the current national boundaries and not according to the boundaries in place at the time of birth. It would then be helpful to have access to additional information in order to be in a position to better identify persons whose country of birth has changed name and/or boundaries and also people who live as national minorities abroad.

1.3.4. Improving the understanding of non-monetary inequalities

The imperative to improve knowledge and understanding also extends to specific aspects of living conditions that may not be adequately captured or reflected in standard measures of poverty, deprivation and exclusion.

In the domain of health and housing, Chapters 10, 11 and 12 illustrate that there is space for a better understanding of EU indicators.

The analysis of unmet medical need in Chapter 10 relies on self-reported unmet need, which it makes clear may be influenced by factors that are unobserved, such as cultural norms and attitudes towards health and illness, health knowledge or literacy, and expectations of health services. These factors are likely to vary across countries, and this has to be borne in mind when comparing the indicator across countries, so it is clearly important to further enhance the understanding of what drives this indicator and develop complementary indicators.

Another strategy to exploit the potential of EU-SILC to improve our understanding of inequality in health is to link EU-SILC data to external sources, to investigate salient outcomes EU-SILC does not capture. In this regard, Chapter 11 provides a striking example of what this can make possible, linking cross-sectional EU-SILC data to information from national mortality registers in later periods for a small subset of European countries. They note that most countries would technically be in a position to make such a link, and that expanding the number of countries and also exploiting the longitudinal information available in EU-SILC on changes in risk factors over time would substantially increase our understanding of the mechanisms linking poverty and mortality risk.

Chapter 12 analyses many different housing dimensions, while emphasising that the available indicators need to be further analysed and for some of them (e.g. housing cost overburden) a revision would be needed.

Chapter 16 also makes valuable use of self-reported health data, in this instance relating to health status, and points out that these are not necessarily accurate proxies for objective health conditions. In another important domain, it also highlights that ideally the number of years of schooling plus life-long learning should be used to compare the educational levels in different countries and would thus be valuable complements to the educational attainment measure.

From an analytical perspective, Chapter 18 shows the potential of EU-SILC to properly construct measures of social class, which is key to deepening understanding of underlying social structures and processes. In addition to identifying specific issues affecting comparability between and within countries over time, the authors recommend that countries should consider collecting ISCO at three- or four-digit level, learning lessons from the European Social Survey (ESS) on how this can be done most efficiently.

1.3.5. Improving the understanding of the impact of social transfers

Another area where improvements in the way key indicators can be constructed from EU-SILC is highlighted in Chapter 7, namely the social indicators that seek to measure the impact of social transfers, an essential element in developing strategies and policies. As that chapter highlights, the current practice of simply deducting gross transfers from disposable income is not appropriate. Ways of deriving transfers net of taxes and social insurance contributions, also accounting for interdependencies between social transfers, need to be found, and discussion of this issue demonstrates that the tax-benefit microsimulation model for the EU (EUROMOD) can play a central role in that regard. In a similar vein, Chapter 3 advocates the use of EUROMOD to correctly impute not only benefits net of taxes but also earnings net of social contributions, filling major information gaps that currently obstruct analysis across countries in a consistent fashion.

At EU level, only the impact of social transfers on disposable income and AROP is monitored. The role of social transfers on non-monetary dimensions (e.g. material deprivation and housing deprivation) should not be omitted and could also be estimated by means of regression-based simulation, as illustrated in Chapter 8 with the MSD indicator.

1.3.6. Improving the understanding of regional disparities

EU-SILC can help to examine key social indicators through a regional rather than national lens, as set out in Chapter 4. At present, this possibility is hampered by the lack of information in the microdata on sample structure and for the identification of regions. The availability (in the UDB), quality and comparability over time of regional identifiers, sampling-related identifiers and person identifiers are crucial in this regard. The approximations employed and described in the chapter to get around these difficulties are not seen as a fully satisfactory solution, so access to existing information needs to be improved, survey designs need to be documented and adapted for regional analysis, and results that use enhanced methods for regional indicators and standard errors should be produced. The chapter argues that, at a minimum, all Member States should provide either NUTS 3- or NUTS 2-level estimates of poverty indicators, disaggregated by urban and non-urban areas, to be disseminated through the Eurostat database and to include an indication of sampling errors, which can be based on average annual approximation (AAA).

1.3.7. Improving the understanding of the dynamics of social problems

The need to improve the measurement and understanding of the dynamics of social problems over time and the longitudinal data required to do so is another major theme emphasised in various chapters. The analysis in Chapter 16 of changes in the level and composition of multidimensional poverty indexes (MPI) over time highlights the value of the longitudinal perspective, and also that extending the scope of such measures to include health, housing and education is highly relevant, not least in the context of the SDGs. However, the results presented were seen as primarily illustrative, as further research on potential biases and how to correct them are flagged as priorities before going further in that direction.

Chapter 15 also points to the value of using longitudinal data for the study of in-work poverty transitions. There are, however, serious constraints on longitudinal analyses imposed by the design of the EU-SILC survey as a 4-year rotational panel. In that respect, the fact that in the revised EU-SILC the length of the rotational panel will be extended from 4 to 6 years, in those countries that will implement the recommendation included in the IESS regulation, is very welcome, as it will offer the possibility of estimating longer phenomena in these countries (the persistent AROP indicator will then be based on a sample size twice as large as that currently available ([10])) and of improving the study of transitions into and out of, and recurrences of, poverty and social exclusion.

In relation to the length of the panel and the structure of the rotational sample, Chapter 17 shows that the rotating panel design employed in EU-SILC can affect the estimates of social indicators and merits further examination. The results identify some rotation group bias in key social indicators in a relatively large number of cases (countries or indicators), leading to inconsistencies between estimates drawn from the longitudinal and from the cross-sectional EU-SILC data sets. Additional analysis of the effects of sampling design characteristics is needed to better understand the nature of the problem, in particular the best combination of register data and selected respondent versus household sampling. These findings highlight the importance of ensuring follow-up over time and of minimising attrition. Monitoring the presence of rotation group bias in key social indicators derived from EU-SILC is simple, and a key recommendation is that it should be part of routine EU-SILC data validation processes.

1.3.8. Improving the understanding of the role of unmeasured factors

Finally, the need to improve understanding of the role of national contextual influences on social problems and address key information gaps obstructing efforts to do so is highlighted in particular in Chapters 8 and 13. The finding that the impact of household-level risk factors on material or housing deprivation is mitigated by a country's GDP per capita suggests that the latter is correlated with hidden contextual factors not included in the analysis. Incorporating some of those factors adequately faces major information problems. Household wealth is one such factor, and linking EU-SILC with data from the Eurosystem Household Finance and Consumption Survey for members of the euro area has major potential in that regard, as demonstrated in the exploratory exercises already coordinated by Eurostat (2020). The scale and quality of public provision of services in areas such as education, healthcare, childcare, eldercare and public transport may also be key, and, while methods to assess their value and role have been the subject of study, this is clearly a key area for further investment of effort, including in enhancing the information available.

1.4. Impact of the COVID-19 pandemic

As emphasised at the outset, the research on which this book reports was carried out before the onset of the COVID-19 pandemic. The pandemic crisis has deep implications for economic and social policies at national and EU levels and for social monitoring, in which EU-SILC will play a central role. Eurostat has proposed a variety of initiatives to cope with the constraints imposed by the crisis on data collection and to measure the socioeconomic impact of the crisis on various social domains, as described in the final chapter of this book. EU-SILC will be an indispensable resource in assessing the impact of the crisis across the entire range of socioeconomic domains when data for 2020 and then 2021 come on stream, allowing the myriad ways in which the pandemic has affected different vulnerable groups and how this has varied across countries to be investigated in depth. These data will also shed light on ways in which EU-SILC can be further developed in future, such as exploiting the potential of subannual alongside annual data collection, and deepening the information provided on access to and

([10]) According to the EU definition, a person is at persistent risk of poverty if they are AROP in the survey year as well as at least 2 of the 3 preceding years.

use of health services and the analysis of the relationships between socioeconomic circumstances and health outcomes. These ongoing interactions between the EU-SILC instrument and emerging social monitoring needs, supported by research, will continue to be critically important.

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2 Investing in statistics: EU-SILC

Emilio Di Meglio, Didier Dupré and Sigita Grundiza ([11])

2.1. Introduction

This chapter introduces the EU-SILC instrument, which is the reference source for comparative statistics on income distribution and social inclusion in the EU. Its aim is to provide the reader of this book with a conceptual and practical insight into the background of this instrument and its main characteristics.

Reliable and timely statistics and indicators, computed from a pan-European harmonised data source and reflecting the multidimensional nature of poverty and social exclusion, are essential for monitoring the social protection and social inclusion process at national and EU levels. Furthermore, the social consequences of the global economic, financial and health crisis caused by the COVID-19 pandemic have given increased importance to data on income distribution, the social situation, and poverty and social exclusion across Europe.

2.2. The EU-SILC instrument and its governance

2.2.1. Scope and geographic coverage

Like most household surveys, EU-SILC covers only people living in private households; persons living in a collective household or an institution are therefore not included in the instrument. This needs to be borne in mind when carrying out statistical analyses and when interpreting indicators, both within a given country and between countries.

EU-SILC was launched in 2003 in seven countries ([12]) and later was gradually extended to all EU countries and beyond. In 2020, the EU-SILC instrument was implemented in 37 countries, namely the 27 EU countries, Albania, Iceland, Kosovo ([13]), Montenegro, North Macedonia, Norway, Serbia, Switzerland, Turkey and the United Kingdom. A pilot took place in Bosnia and Herzegovina in 2019, and full survey implementation is planned for 2021. Small areas of the national territory of some of these countries, amounting to no more than 2 % of the national population, are excluded from EU-SILC, as are the following national territories: the French overseas departments and territories, the Dutch West Frisian Islands with the exception of Texel, and lastly the Scilly Islands.

In 2019, 297 000 households and 611 000 individuals were interviewed for EU-SILC and the complete microdata were sent to Eurostat.

2.2.2. Main characteristics of EU-SILC

All EU Member States are required to implement EU-SILC, which is based on the idea of a common

([11]) All Eurostat. Address for correspondence: estat-secretariat-F4@ec.europa.eu. The European Commission bears no responsibility for the analyses and conclusions, which are solely those of the authors.

([12]) Austria, Belgium, Denmark, Greece, Ireland, Luxembourg and Norway.

([13]) This designation is without prejudice to positions on status, and is in line with UN Security Council Resolution 1244 and the International Court of Justice Opinion on the Kosovo Declaration of Independence.

framework as opposed to a common survey. The common framework consists of common procedures, concepts and classifications, including harmonised lists of target variables to be transmitted to Eurostat.

Two types of annual data are collected through EU-SILC and provided to Eurostat.

- Cross-sectional data pertaining to a given time period, including variables on income, poverty social exclusion and other living conditions. The data for the survey of year N are currently to be transmitted to Eurostat by November of year (N + 1), even if many countries manage to send the data before this deadline. In 2020, for example, 16 countries sent their 2019 data by the end of June 2020; and, by the end of October 2020, EU indicators were published for 27 countries.
- Longitudinal data pertaining to changes over time at individual level are observed periodically over a 4-year period. Longitudinal data are confined to income information and a reduced set of other variables, designed to identify the incidence and dynamic processes of persistent poverty and social exclusion among subgroups of the population. The longitudinal data corresponding to the period between year (N – 3) and year N are currently to be transmitted to Eurostat by March of year (N + 2). Many countries managed to send longitudinal weights in advance, together with the cross-sectional transmission.

With the entry into force of the IESS regulation in 2021 (see Chapter 20 for more details on IESS), this calendar of transmission will be modified and data will have to be transmitted by December of year N as from 2021. Longitudinal data will have to be transmitted by October of year N + 1. To those countries that had launched a new survey, Eurostat proposed an integrated design with a 4-year rotational panel. That involves a new sample (panel) being selected each year and included in the survey for 4 years. Each new sample (replication) is similar in size and design, and representative of the whole population. Thus, in year N, the panels from years N – 1, N – 2 and N – 3 are retained, while the panel selected in year N – 4 is dropped and replaced with a new one.

The fundamental characteristic of the integrated design is that the cross-sectional and longitudinal statistics are produced from essentially the same set of sample observations ([14]), thus avoiding the unnecessary duplications that would be involved if entirely separate cross-sectional and longitudinal surveys were used.

2.2.3. Legal basis

One of the strengths of the EU-SILC instrument is the existence of a legal basis that is binding on EU Member States and a requirement for candidate and potential candidate countries. The development of the common framework, including the conception of the annual ad hoc modules (see below), is discussed on a permanent basis with the main stakeholders, in particular within the EU Working Group for Statistics on Living Conditions, chaired by Eurostat. Given that the new IESS legal basis entered into force in 2021, the focus in this chapter is on the pre-2021 EU-SILC framework.

The EU-SILC legal basis used until the implementation of IESS (hence for the data analysed in this book) consists of three main components.

1. A framework regulation ([15]), which covers the scope, definitions, time reference, characteristics of the data, data required, sampling rules, sample sizes, transmission of data, publication, access for scientific purposes, financing, reports and studies for the EU-SILC instrument. This regulation was amended by Regulation (EC) No 1553/2005 ([16]) and Council Regulation (EC) No 1791/2006 ([17]) in order to extend the EU-SILC instrument to include the new Member States.

([14]) Currently only the United Kingdom derives cross-sectional and longitudinal data from two different survey instruments.
([15]) Regulation (EC) No 1177/2003 of the European Parliament and of the Council of 16 June 2003 concerning Community statistics on income and living conditions (EU-SILC).
([16]) Regulation (EC) No 1553/2005 of the European Parliament and of the Council of 7 September 2005 amending Regulation (EC) No 1177/2003 concerning Community statistics on income and living conditions (EU-SILC).
([17]) Council Regulation (EC) No 1791/2006 of 20 November 2006 adapting certain Regulations and Decisions by reason of the accession of Bulgaria and Romania.

2. Five Commission regulations, which specify some technical aspects of the instrument: definitions ([18]), fieldwork aspects and imputation procedures ([19]), sampling and tracing rules ([20]), list of primary (annual) target variables ([21]) and quality reports ([22]).
3. Annual Commission regulations on the list of secondary target variables, that is, the ad hoc thematic modules, which cover a different topic each year and can be repeated after 5 years or less, but no systematic repetition is set up.

The EU-SILC instrument is also applicable to Iceland, Norway, Switzerland and the United Kingdom. For candidate and potential candidate countries, the implementation of EU-SILC is not compulsory until they join the EU, but it is strongly encouraged if the specific situation of a given country so permits.

2.2.4. Common guidelines

The way to implement the EU-SILC legal basis is agreed between Eurostat and the national statistical institutes (NSIs), in particular in the EU Working Group for Statistics on Living Conditions and the task forces reporting to it ([23]). This includes common procedures and concepts, as well as an increasing number of recommendations on how to word the underlying questions. The full set of guidelines is available to the public ([24]). The guidelines are updated yearly in order to fine-tune the data collection on particular topics or in order to further improve methodological issues with the final aim of continuously improving the comparability between countries, and are agreed by the working group.

Strategic issues regarding the development of EU-SILC are discussed in the meetings of the European Statistical System Committee (ESSC ([25])) and the NSIs' directors of social statistics.

2.3. Methodological framework

2.3.1. Contents of EU-SILC

EU-SILC is a multidimensional instrument focused on income. It also covers housing, labour, health, demography, education and deprivation, to allow for the analysis of the multidimensional phenomena of poverty and social exclusion, and for the joint analysis of its different dimensions. It consists of primary (annual) and secondary (ad hoc modules) target variables, all of which are forwarded as microdata sets by Member States to Eurostat.

Given the principle of flexibility of the implementation of EU-SILC at national level, the sequence of questions needed to construct one target variable may vary from country to country. Nevertheless, recommended wordings of questions are available for the ad hoc modules and a number of primary variables (such as health and material deprivation variables), although countries are not obliged to follow these recommendations.

([18]) Commission Regulation (EC) No 1980/2003 of 21 October 2003, updated by Commission Regulation (EC) No 676/2006, implementing Regulation (EC) No 1177/2003 as regards definitions and updated definitions.
([19]) Commission Regulation (EC) No 1981/2003 of 21 October 2003 implementing Regulation (EC) No 1177/2003 as regards the fieldwork aspects and the imputation procedures.
([20]) Commission Regulation (EC) No 1982/2003 of 21 October 2003 implementing Regulation (EC) No 1177/2003 as regards the sampling and tracing rules.
([21]) Commission Regulation (EC) No 1983/2003 of 7 November 2003 implementing Regulation (EC) No 1177/2003 as regards the list of target primary variables.
([22]) Commission Regulation (EC) No 28/2004 of 5 January 2004 implementing Regulation (EC) No 1177/2003 as regards the detailed content of intermediate and final quality reports.
([23]) These task forces support the work of the EU Working Group for Statistics on Living Conditions. For instance, the Task force on the revision of the EU-SILC legal basis provided a major contribution to the development of IESS. The set of secondary variables included in EU-SILC modules is generally prepared by an ad hoc task force. Important work on the development of a set of material deprivation variables and of related EU social indicators was performed by the Task force on material deprivation.
([24]) See in particular annual guidelines available on Communication and Information Resource Centre for Administrations, Businesses and Citizens (CIRCABC) (http://circabc.europa.eu) in the EU-SILC dedicated interest group.
([25]) The ESSC is at the heart of the European Statistical System. It is chaired by Eurostat and composed of the representatives of Member States' NSIs. The European Free Trade Association (EFTA) countries (Iceland, Liechtenstein, Norway and Switzerland) and the EFTA Statistical Office participate as observers. Observers from the European Central Bank (ECB), Organisation for Economic Co-operation and Development (OECD), etc. may also participate in the meetings of the ESSC. The ESSC meets three times a year.

The primary target variables relate to either household or individual (for persons aged 16 or more) information and are grouped into five areas:

- at household level – basic/core data, income, housing, social exclusion and labour information;
- at personal level – basic/demographic data, income, education, labour information and health.

The secondary target variables are introduced and sometimes repeated after some years, only in the cross-sectional component. One ad hoc module per year has been included since 2005 ([26]):

- 2005 – intergenerational transmission of poverty;
- 2006 – social participation;
- 2007 and 2012 – housing conditions;
- 2008 – overindebtedness and financial exclusion;
- 2009 and 2014 – material deprivation;
- 2010 – intra-household sharing of resources;
- 2011 – intergenerational transmission of disadvantages;
- 2013 – well-being;
- 2015 – social/cultural participation and material deprivation;
- 2016 – access to services;
- 2017 – health and children's health
- 2018 – material deprivation, well-being and housing difficulties;
- 2019 – intergenerational transmission of disadvantages, household composition and change in income;
- 2020 – overindebtedness, consumption and wealth as well as labour.

([26]) For detailed information on the content of these modules, see Eurostat (https://ec.europa.eu/eurostat/web/income-and-living-conditions/data/ad-hoc-modules).

2.3.2. Income concept

An important objective for EU-SILC is to adhere as closely as possible to the recommendations of the international Canberra Group on the definition of household income (see United Nations Economic Commission for Europe, 2011). The income concept in the sense of the Canberra recommendations has been fully implemented since 2007 in EU-SILC.

Two main aggregates are computed from EU-SILC: total gross household income (GI) and total disposable household income (DI), which are defined as:

$$GI = EI + SEI + PP + CTR + OI$$

$$DI = GI - CTP$$

where:

EI = employee income (cash or near-cash employee income and non-cash employee income

SEI = self-employment income (but not goods produced for own consumption)

PP = pensions received from individual private plans

CTR = current transfers received (social benefits and regular inter-household cash transfers received)

OI = other sources of income received (such as capital income)

CTP = current transfers paid (tax on income and social insurance contributions, tax on wealth and regular inter-household cash transfers paid).

Employee income

In EU-SILC, employee income is covered by the collection of information on 'Gross cash or near-cash employee income', 'Gross non-cash employee income' and 'Employers' social insurance contributions'. For non-cash employee income, only company cars have been recorded since the beginning of EU-SILC and included in the income concept. Information covering all other goods and services provided free of charge or at reduced price by employers to their employees, and the compulsory component of employers' social insurance contributions, are to be collected, but are not yet included in the main income aggregates.

Self-employment income

Self-employment income is broken down into 'Gross cash profits or losses from self-employment' (including royalties) and 'Value of goods produced for own consumption'. Various alternative approaches to the measurement of income from self-employment are allowed. The value of goods produced for own consumption is not included in the main income aggregates.

Private pension plans

Regular pensions from private plans – other than those covered within the 'Current transfers' item – are pensions and annuities received in the form of interest or dividend income from individual private insurance plans, that is, fully organised schemes where contributions are at the discretion of the contributor independently of their employers or government.

Current transfers received

Current transfers received include social benefits and regular inter-household cash transfers received. Social benefits are broken down into family- and child-related allowances, housing allowances, unemployment benefits, old age benefits, survivors' benefits, sickness benefits, disability benefits, education-related allowances and 'other benefits not elsewhere classified'.

Other sources of income received

Three sources of income are covered under this item:

- income from rental of a property or land;
- interest, dividends, profits from capital investment in unincorporated business;
- income received by people aged under 16.

Current transfers paid

Current transfers paid are broken down into 'Tax on income and social insurance contributions', 'Regular taxes on wealth' and 'Regular inter-household cash transfers paid'. The 'Employers' social insurance contributions' variable is not included in the computation of the main income aggregates, even though it would be crucial for cross-country comparisons related to labour cost.

Imputed rent

The imputed rent has been collected from 2007 onwards for all households that do not report that they pay full rent, that is, households that own the dwelling they live in (owner-occupiers) or households that enjoy subsidised rents. However, the value of imputed rent is not included in the main income aggregates. Its inclusion would have a significant impact on all income-based indicators, but a methodology for obtaining comparable results for all countries is not yet available ([27]). For a discussion on the distributional impact of imputed rent in EU-SILC and the lack of cross-country comparability of this component, see Törmälehto and Sauli (2017).

Imputation

The EU-SILC framework requires full imputation for income components. The level of imputation of income components is reported in microdata by means of a set of detailed flags. This requirement helps to make the information delivered by the instrument more homogeneous and complete. Imputation is performed by Member States.

Income reference period

In all but two countries, Ireland and the United Kingdom, the income reference period is the previous calendar year. So, for a survey conducted in year N the income information that is collected refers to the household income received between 1 January N – 1 and 31 December N – 1 (put differ-

([27]) The position of the SPC indicators subgroup is that the imputed rent component could be included in a small number of income poverty indicators, which would be listed in the EU social inclusion portfolio as secondary indicators or context information.

ently, the survey year is N and the income year is N – 1). Ireland and the United Kingdom use a sliding reference period. In Ireland, it refers to the 12 months prior to the interview date. In the United Kingdom, it is centred on the interview date, meaning it covers 6 months before and 6 months after the interview. In addition, the respondents are asked to provide figures that relate most commonly to their current (and usual) incomes, which could relate to the last week, 2 weeks or month. These figures are then annualised.

The more distant in time the fieldwork period is from the income reference period, the higher the risk of inconsistency between income-related variables and other socioeconomic variables (including sociodemographic variables). It is therefore essential to limit as much as possible the lag between the income reference period and the fieldwork, by conducting the interviews preferably in the first quarter of the year.

Equivalised income

Most income-based EU social indicators are computed using an equivalised disposable income, which is calculated in three steps.

1. All monetary incomes received from any source by each member of a household are added up (these include income from work, investment and social benefits, plus any other household income; taxes and social contributions that have been paid are then deducted from this sum).
2. In order to reflect differences in a household's size and composition, the total (disposable) household income is divided by the number of 'equivalent adults', using the OECD-modified (equivalence) scale, which gives a weight to all members of the household (1 to the first adult, 0.5 to the second and each subsequent person aged 14 and over, and 0.3 to each child aged under 14).
3. Finally, the resulting figure, the equivalised disposable income, is attributed to each member of the household (adults as well as children). This means that, for a couple and two children, income is divided by 2.1 (1 + 0.5 + 0.3 + 0.3), so that an annual income of EUR 10 500 becomes an equivalised income of EUR 5 000, which is artificially assigned to each of the four household members (i.e. including each of the two children).

2.3.3. Sample requirements

Sampling design

EU-SILC data are to be collected from nationally representative probability samples of the population residing in private households within the country, irrespective of language, nationality or legal residence status. All private households and all persons aged 16 and over within the household are eligible for the operation. Representative probability samples must be achieved both for households and for individual persons in the target population. The sampling frame and methods of sample selection should ensure that every individual and household in the target population is assigned a known probability of selection that is not zero.

Sample size

The framework regulation and its updates define the minimum effective sample sizes to be achieved. The effective sample size is the size that would be required if the survey were based on simple random sampling (design effect in relation to the EU AROP indicator = 1.0). The actual sample sizes have to be larger to the extent that the design effect exceeds 1.0, because of complex sampling designs and in order to compensate for all kinds of non-response. The sample sizes for the longitudinal component refer, for any 2 consecutive years, to the number of households or individuals aged 16 and over that are successfully interviewed in both years. Table 2.1 gives the minimum effective sample sizes required for each EU Member State (plus Iceland, Montenegro, North Macedonia, Norway, Serbia, Switzerland, Turkey and the United Kingdom) in terms of households and individuals aged 16 or over.

Table 2.1: Minimum effective sample size for the cross-sectional and longitudinal components

Country	Households		Persons aged 16 or over to be interviewed	
	Cross-sectional	Longitudinal	Cross-sectional	Longitudinal
Belgium	4 750	3 500	8 750™	6 500
Bulgaria	4 500	3 500	10 000	7 500
Czechia	4 750	3 500	10 000	7 500
Denmark	4 250	3 250	7 250	5 500
Germany	8 250	6 000	14 500	10 500
Estonia	3 500	2 750	7 750	5 750
Greece	4 750	3 500	10 000	7 250
Spain	6 500	5 000	16 000	12 250
France	7 250	5 500	13 500	10 250
Croatia	4 250	3 250	9 250	7 000
Ireland	3 750	2 750	8 000	6 000
Italy	7 250	5 500	15 500	11 750
Cyprus	3 250	2 500	7 500	5 500
Latvia	3 750	2 750	7 650	5 600
Lithuania	4 000	3 000	9 000	6 750
Luxembourg	3 250	2 500	6 500	5 000
Hungary	4 750	3 500	10 250	7 750
Malta	3 000	2 250	7 000	5 250
Netherlands	5 000	3 750	8 750	6 500
Austria	4 500	3 250	8 750	6 250
Poland	6 000	4 500	15 000	11 250
Portugal	4 500	3 250	10 500	7 500
Romania	5 250	4 000	12 750	9 500
Slovenia	3 750	2 750	9 000	6 750
Slovakia	4 250	3 250	11 000	8250
Finland	4 000	3 000	6 750	5 000
Sweden	4 500	3 500	7 500	5 750
Total EU	127 500	95 750	268 400	200 350
Iceland	2 250	1 700	3 750	2 800
Norway	3 750	2 750	6 250	4 650
Switzerland	4 250	3 250	7 750	5 800
United Kingdom	7 500	5 750	13 750	10 500
Montenegro	3 250	2 500	8 750	6 500
North Macedonia	3 750	3 000	11 500	8 750
Serbia	4 500	3 500	ND	ND
Turkey	7 750	5 750	21 000	ND

Note: ND: not defined.

Sources: Regulations (EC) Nos 1553/2005 and 1791/2006 of the European Parliament and of the Council. For candidate countries, the minimum effective sample size is not regulated.

2.3.4. Tracing rules

In order to ensure the best-quality output, minimum requirements for implementation have been defined within the legal basis in addition to the definition of the minimum sample size. These rules concern, for instance, the use of proxy interviews, the use of substitutions, fieldwork duration, non-response procedures and tracing (or following) rules.

In each country, the longitudinal component of EU-SILC consists of one or more panels or subsamples (four subsamples in the recommended 4-year rotational design). For each panel/subsample, the initial households representing the target population at the time of its selection are followed for a minimum of 3 years on the basis of specific tracing rules. The objective of the tracing rules is to follow up individuals over time.

In order to study changes over time at individual level, all sample persons (members of the panel/subsample at the time of their selection) should be followed up over time, even though they may move to a new location during the life of the panel/subsample. However, in the EU-SILC implementation, some restrictions are applied owing to cost and other practical reasons. Only those persons staying in one private household or moving from one to another in the national territory are followed up. Sample persons moving to a collective household or to an institution, moving to national territories not covered in the survey or moving abroad (to a private household, collective household or institution, within or outside the EU), would normally not be traced. The only exception would be the continued tracing of those moving temporarily (for an actual or intended duration of less than 6 months) to a collective household or institution within the national territory covered, as they are still considered household members. Tracing rules will change with the entry into force of the IESS regulation.

2.4. Information on quality

2.4.1. Some comparability issues

The flexibility of the EU-SILC instrument may be seen as both its main strength and its main weakness. While flexibility allows EU-SILC to be embedded into the national systems of social surveys, it can create problems of harmonisation and comparability across countries. This section addresses some of these comparability issues.

Different sampling designs

Almost all countries have used the integrated design proposed by Eurostat.

The EU-SILC framework encourages the use of existing sources and/or administrative data. However, in practice, not all EU-SILC variables can be obtained from registers and administrative data. Hence, it is possible to establish two groups of countries on the basis of the data source used in EU-SILC.

- In the countries referred to as 'register' countries (Denmark, Finland, Iceland, the Netherlands, Norway, Slovenia, Sweden), most income components and some items of demographic information are obtained through administrative registers. Other personal variables are obtained by means of interview from a sample of persons according to the 'selected respondent model', in which only one member of the household answers the detailed questionnaire, while the income information is derived from register data for all household members. More and more countries are moving towards retrieving income information from registers, but without moving to the selected respondent model. This is the case for Belgium, Cyprus, Estonia, Spain, France, Italy, Latvia, Malta and Austria, which use registers and/or a combination of register and survey data to construct some income variables (see Zardo Trindade and Goedemé, 2020).
- In other countries, the full information is obtained by means of a survey of households and interviews with household members.

All the national sampling designs ensure strict cross-sectional representativeness and enable a significant number of individuals to be followed over a period of at least 4 years. In line with the legal requirements, all samples are probabilistic ([28]), with updated sampling frames and stochastic algorithms used to select statistical units. The sampling designs used in 2018 by country were the following:

- sampling of dwellings or addresses – Albania, Austria, Croatia, Czechia, France, Hungary, Latvia, the Netherlands, Poland, Portugal, Romania, Spain and the United Kingdom;
- sampling of households – Belgium, Bulgaria, Cyprus, Denmark, Germany, Greece, Ireland, Italy, Kosovo, Luxembourg, Malta, Serbia, Slovakia and Switzerland;
- sampling of individuals – Estonia, Finland, Iceland, Lithuania, Norway, Slovenia and Sweden (all these countries are register countries except for Estonia and Lithuania).

In all cases, sample unbiased estimates can be produced on firm theoretical grounds. In almost all countries, the coverage bias is controlled with frequent updates of the frame.

Countries have designed their samples to achieve a good trade-off between reporting needs at subnational level and the cost effectiveness of the data collection. Significant increases in the sample size, driven by subnational reporting requirements in view of the new framework regulation concerning EU-SILC, adopted in October 2019 (see Chapter 20), were recorded in Greece and Portugal and are planned in other countries.

Differences in the method of data collection

In most countries (i.e. the non-register countries), all members aged 16 or over in selected households are asked to respond to a personal questionnaire, whereas in the register countries only one selected respondent per household receives a personal questionnaire. These two different rules have different impacts on the tracing of individuals over time (longitudinal dimensions) depending on whether only one or all household members are interviewed over time. The selected respondent model needs some adaptation in order to avoid bias in the follow-up of children. The two different rules lead to different weighting schemes. In particular, when the selected respondent type is used, the weights of the household and of the selected respondent are obviously different.

In 2018, the most frequent mode of data collection was computer-assisted personal interview (CAPI), used as the primary mode in 16 countries (Belgium, Bulgaria, Cyprus, Estonia, Ireland, Spain, France, Croatia, Italy, Latvia, Luxembourg, Hungary, Malta, Austria, Poland and Portugal). It was followed by paper and pencil interview (PAPI), used as the primary mode in 4 countries (Czechia, Greece, Romania, Slovakia), and computer-assisted telephone interview (CATI), also used in 4 countries (Lithuania, Slovenia, Finland and Sweden); and then computer-assisted web interview (CAWI), used in 2 countries (Denmark and the Netherlands). Self-administered paper questionnaire, used in some countries as a residual mode, is used as the primary mode in Germany. Some other countries are testing web questionnaires and some are testing mixed modes.

Different non-response rates

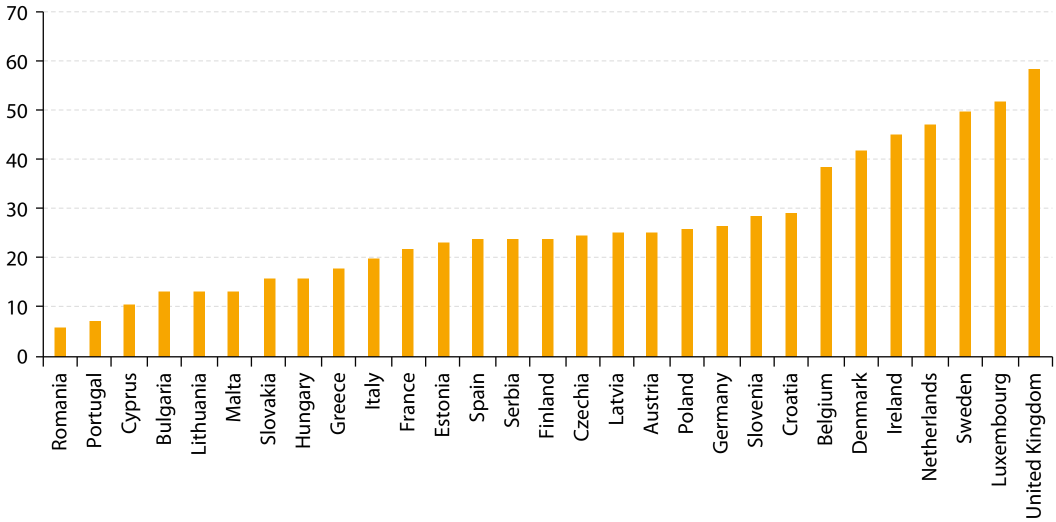
Non-response is measured in EU-SILC at three stages: address contact, household interview and personal interview. Figure 2.1 presents the overall non-response rates for individuals for the whole sample broken down by country.

Total non-response of the selected households and individuals had to be less than 40 %, which was seen as a challenge for a non-mandatory survey. The overall non-response rate in the personal interview for the whole sample of EU-27 Member States was equal to or below 10 % in 2018 in three countries: Romania (6 %), Portugal (7 %) and Cyprus (10 %). At the other extreme, non-response rates exceeded 30 % in six countries and even 50 % in Luxembourg (51.7 %); for non-EU countries for which information is currently available, it was 24 % in Serbia and 58 % in the United Kingdom.

The creation of models using external variables in order to correct for non-response is highly desira-

([28]) Germany used quota sample by derogation until 2008.

Figure 2.1: Overall personal non-response rates, 2018
(%)



Note: Countries are ranked according to their level of response rate.
Sources: EU-SILC country quality reports.

ble. Most of the countries apply either a standard post-stratification, based on homogeneous response groups, or a more sophisticated logistic regression model.

2.4.2. Quality reports

Adopted in 2005, the European Statistics Code of Practice sets common standards for the independence, integrity and accountability of the national and EU statistical authorities. The EU statistical authorities have undertaken to adopt a comprehensive approach to high-quality statistics that builds upon a common definition of quality in statistics, in which the following dimensions are addressed.

- Relevance: European statistics must meet the needs of users.
- Accuracy and reliability: European statistics must accurately and reliably portray reality.
- Timeliness and punctuality: European statistics must be disseminated in a timely and punctual manner.
- Coherence and comparability: European statistics should be consistent internally and over time, and comparable between regions and countries; it should be possible to combine and make joint use of related data from different sources.
- Accessibility and clarity: European statistics should be presented in a clear and understandable form, disseminated in a suitable and convenient manner, and available and accessible on an impartial basis with supporting metadata and guidance.

This European definition of quality is monitored in EU-SILC, with annual quality reports prepared by both the countries and, for the EU level, Eurostat, and managed through an integrated IT system.

The national quality reports provide a useful insight into national implementation practice as well as substantive information from which to draw preliminary conclusions regarding the quality of the instrument. This material is complemented by the information that Eurostat collects through its frequent contacts with national statistical authorities, in particular as regards data validation, which is an integrated process using tools shared with Member States.

The purpose of the EU quality reports is to summarise the information contained in the national quality reports. Their objective is to evaluate the quality of the instrument from a European perspective, by establishing cross-country comparisons of some of its key quality characteristics.

The EU quality reports, as well as most of the national country reports, are publicly available ([29]).

2.5. Data and indicators

2.5.1. Data access

EU-SILC data are disseminated either as aggregated data or as microdata sets. Individual EU-SILC records are considered confidential data within the meaning of Article 23 of the Statistical Law ([30]) because they allow indirect identification of statistical units (individuals and households). In this context, they should be used only for statistical purposes or for scientific research.

Aggregated results relate to indicators and statistics on income distribution and monetary poverty, living conditions, material deprivation and childcare arrangements. They are presented as predefined tables or as multidimensional data sets and may be extracted in a variety of formats ([31]).

Commission Regulation (EU) No 557/2013 ([32]) granted the European Commission permission to release anonymised microdata to researchers. Anonymised microdata are defined as individual statistical records that have been modified in order to control, in accordance with best practices, the risk of identification of the statistical units to which they relate. Both EU and national rules are applied for anonymisation, and are described in full with each release. The modifications involve variable suppression, global recoding and the randomisation of some variables.

Twice a year Eurostat releases anonymised microdata to researchers (files available via secure CIRCABC). Each release contains data from the latest available operation, as well as revisions from any previous data sets. A detailed description of the full procedure for accessing microdata is provided on the Eurostat website ([33]).

2.5.2. Indicators computation

In order to monitor progress towards the Europe 2020 strategy, an analytical tool has been put in place: the joint assessment framework (JAF). The JAF underpins evidence-based policymaking in the social domain. In particular, it is used as an analytical tool in the dialogue between the Commission and the Member States to support the identification of key challenges and help Member States establish their priorities. In each policy area, progress in the implementation of policies and towards the related EU social objectives is assessed quantitatively on the basis of a limited number of commonly agreed indicators. A large number of indicators are computed on the basis of EU-SILC, which has become the second pillar of household social survey statistics at EU level, complementing the EU Labour Force Survey, which focuses on labour market information.

The use of commonly agreed indicators (not only in the context of the JAF but also, more widely, to analyse the social situation across the EU and monitor progress towards the commonly agreed EU social objectives) is an essential component of EU cooperation in the social field. The development of EU social indicators is a dynamic process, which is the responsibility of the SPC and its indicators subgroup. The work of the national delegations of experts, who make up the subgroup, and the secretariat provided by the European Commission's Directorate-General for Employment, Social Affairs

([29]) http://circabc.europa.eu, EU-SILC interest group quality folder.
([30]) Regulation (EC) No 223/2009 of the European Parliament and of the Council of 11 March 2009 on European statistics and repealing Regulation (EC, Euratom) No 1101/2008 of the European Parliament and of the Council on the transmission of data subject to statistical confidentiality to the Statistical Office of the European Communities, Council Regulation (EC) No 322/97 on Community Statistics, and Council Decision 89/382/EEC, Euratom establishing a Committee on the Statistical Programmes of the European Communities.
([31]) Data and publications can be accessed at: http://ec.europa.eu/eurostat/web/income-and-living-conditions
([32]) Commission Regulation (EU) No 557/2013 of 17 June 2013 implementing Regulation (EC) No 223/2009 of the European Parliament and of the Council on European Statistics as regards access to confidential data for scientific purposes and repealing Commission Regulation (EC) No 831/2002.
([33]) http://ec.europa.eu/eurostat/web/microdata/overview

and Inclusion (in close cooperation with Eurostat) has enabled the set of indicators (and breakdowns of them) to be considerably enriched.

EU social indicators are grouped in four portfolios: an overarching portfolio and a portfolio for each of the three main social areas in which Member States cooperate (poverty and social exclusion; pensions; and healthcare and long-term care) ([34]). The indicators are continually updated and disseminated on the Eurostat website ([35]).

2.6. Way forward

Even though EU-SILC has become the EU reference for data on income and living conditions, Eurostat and a number of stakeholders are reflecting on ways to further improve the tool and its (potential) uses. This book, and more generally the analysis and activities of Net-SILC3, which prepared it, are part of an effort to improve EU-SILC and the development and analysis of social indicators based on it.

As mentioned above, a revision of the legal basis of EU-SILC is now being implemented. The main objectives of the revision are:

- in the context of the modernisation of social statistics, integrate EU-SILC with other data collection operations, standardise variables and modules, use administrative data sources more widely and improve statistical frames;
- increase the responsiveness of the instrument to new policy needs, currently and for the future;
- deliver EU-SILC data faster;
- maintain the stability of the main indicators, with adapted frequency and keeping a cross-cutting approach;
- maintain or, if possible, slightly decrease the current burden and costs;
- allow sufficient regional breakdown;
- ensure adequate accuracy and quality of measurements;
- adapt to multimode and multisource data collection operations;
- ensure general consistency of the different elements of the tool (e.g. frequency of non-annual modules and length of the longitudinal component).

The future developments of EU-SILC itself and the new legal basis are presented in detail in Chapter 20.

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Zardo Trindade, L. and Goedemé, T. (2020), 'The comparability of the EU-SILC income variables: review and recommendations', *Statistical Working Papers*, Publications Office of the European Union, Luxembourg.

([34]) More information on the EU social indicators can be found on the Employment, Social Affairs and Inclusion website (http://ec.europa.eu/social/main.jsp?catId=830&langId=en). See also Social Protection Committee (2015).
([35]) https://ec.europa.eu/eurostat/web/main/data/database

Improving our understanding of inequalities

3 Exploring inequality decomposition by income source at EU level

Stefano Filauro and Alessia Fulvimari ([36])

3.1. Introduction

The austerity measures implemented by EU Member States following the European debt crisis have increased inequality concerns in the EU. As a result, there is an increasing focus on the underlying mechanisms that cause inequality, with attention also being given to the possible negative socioeconomic impact of income inequality. Public policy is increasingly focusing on the economic processes that cause income inequalities. In particular, it is focusing on the extent to which market income sources determine current inequality levels and the extent to which these levels can be mitigated by taxes and benefits. Policies to counteract income inequality must be informed by the different market and welfare mechanisms in different EU countries ([37]). If labour market and capital market processes are responsible for a surge in income inequality, policy action should focus on a mix of 'pre-market' policies (i.e. policies that focus on endowments and the quality of education and health systems) and 'in-market policies' (i.e. policies that focus on inclusive and well-regulated labour markets, open product markets and efficient credit markets). Otherwise, if the growth in inequality is due to the welfare state being less effective in curbing inequality, policy action should focus more on redistributive tax systems and on income support through benefit systems. In the first case, authority for both pre-market and in-market policies is split between the national level and the EU level. In the second case, responsibility for income support through tax and benefit systems lies mostly at national level.

Previous studies on the EU have largely addressed the role of different market income and welfare income sources in income inequality over the last 15 years. These studies have been helped by EU-SILC and its predecessor, the European Community Household Panel (ECHP). The general trend of income inequality in the EU seems to point to a slight increase in the immediate aftermath of the financial crisis followed by a broadly stationary inequality trend. The consensus view is that market mechanisms (particularly those related to the labour market) are responsible for the increase in inequality experienced in many EU countries after the crisis, while the inequality-reducing effect of the welfare state is increasingly under pressure (OECD, 2015). Recent research points to the role of increasingly unequal market incomes in causing income inequality to rise (Jenkins et al., 2012; Callan et al., 2018). However, researchers have also examined in detail the role of different taxes and benefits in alleviating income inequality (Leventi et al., 2019). Clearly, these trends took shape in very different ways across the EU. Nonetheless, in the years of recovery since the crisis, many countries reduced the impact of fiscal stabilisers. This was mostly due to fiscal consolidation, as EU countries reduced benefit expenditure and raised taxes (not always in a progressive way).

([36]) Both European Commission, Directorate-General for Employment, Social Affairs and Inclusion. We would like to thank Elena Bárcena Martín and the editors for their very useful comments and their constant support. All errors remain our own. The views expressed in the text are the private views of the authors and may not, under any circumstances, be interpreted as stating an official position of the European Commission. Email address for correspondence: stefano.filauro@ec.europa.eu

([37]) See European Commission (2019) for an overview of both market and welfare policies to tackle income inequality.

Against this framework, this chapter intends to (1) shed light on the overall changes in effects of market income and welfare income sources (whether these sources increase or reduce income inequality) and (2) track potential common patterns across EU countries with EU-SILC data. Previous studies have carried out inequality decompositions by income sources to distinguish the effects of the different income sources. For instance, Garcia-Peñalosa and Orgiazzi (2013) and Raitano (2016) apply an inequality decomposition by income source to specific EU countries or clusters of countries in a comparative analysis. In this study, we apply this same type of inequality decomposition to the EU countries in two particular periods: the recession and its immediate aftermath (2008–2013) and the subsequent recovery (2013–2018). Owing to the data limitations in comparing the **levels** of the inequality contributions of the different income sources between countries, we focus on their corresponding **changes** in the two periods and assess the trend over time to see if they increased or reduced income inequality. Thus, we assume that within-country percentage changes of the source contributions over time are more comparable than their levels if data quality does not vary over time. This is a different approach from previous studies, which mainly compared **levels** of source contributions across countries. In passing, we discuss the data limitations in EU-SILC that make it difficult to uncover inequality contributions from different income sources that are fully comparable across countries or over time. The chapter is organised as follows: Section 3.2 describes the methods used to decompose disposable income inequality by income sources; Section 3.3 illustrates the income concepts used and discusses some data limitations affecting the inequality decomposition; Section 3.4 presents the results of the inequality decomposition; and Section 3.5 summarises and concludes.

3.2. Methods

Previous studies that addressed the role of market sources against welfare sources to determine income inequality have often used inequality decomposition by income source (38). As pioneered by Shorrocks (1982), there are infinite decomposition rules by which overall income inequality in a given year I may be expressed as the sum of inequality contributions from each of the income sources. Let us suppose that there are k different income sources that constitute disposable household income, whose corresponding income inequality level may be expressed as:

$$I = \sum_k S_k$$

It follows that $\sum_k s_k = 1$, so that S_k is the absolute inequality contribution of source k, while s_k is the proportional contribution. Shorrocks (1982) proposes a unique decomposition rule obtained by imposing two restrictions on the choice of decomposition method. This rule turns out to be the natural decomposition of the variance and the squared coefficient of variation. According to this rule, the proportion of income inequality contributed by source k can be computed as:

$$s_k = \frac{cov(Y_k, Y)}{\sigma^2(Y)}$$

That is, the proportional inequality contribution of each source k is the covariance between income source k and disposable income (Y) over the disposable income variance (39). Thus, it stems from the equation that in this decomposition the level of the contribution of the income source depends on (1) the share of the income source in total income; (2) the equality/inequality level of the income source; (3) the correlation of the income source with household disposable income. These three aspects are central in the interpretation of the inequality contributions. Income sources with a positive contribution to inequality ($s_k > 0$) have a 'disequalising' impact (i.e. they increase inequality) and the converse is true of sources with a negative contribution ($s_k < 0$), which reduce inequality (40).

(38) In previous theoretical and empirical studies the terms 'source', 'factor' and 'component' are used rather interchangeably. For the sake of consistency, we use 'source' throughout the study.
(39) It is also the slope coefficient derived from a regression of aggregate income over the specific income source k.
(40) Intuitively, if an income source is positively correlated with overall disposable income, it contributes positively to income inequality (i.e. it increases inequality) and it contributes negatively if it is negatively correlated. For example, in the case of taxes, those who pay higher taxes are usually those with higher household income. Thus the correlation with household income is negative and the taxes' effect on inequality is mitigating.

Sources with zero contribution are equally distributed across the population. In general, there is a fair degree of correspondence between the size of the inequality contribution of an income source and its share in aggregate income, but the ratio is far from identical for all income sources (Shorrocks, 1983). The two counterfactual interpretations for each absolute contribution S_k are derived from the restrictions imposed on the decomposition rule. They might be regarded as (1) the inequality that would be observed if all income sources had an egalitarian distribution, but source *k* were uniquely responsible for overall inequality, and (2) the amount by which inequality would decrease if source *k* were equally distributed.

Inequality decompositions by income source have primarily been used to determine the inequality contribution of different income sources at a particular point in time (see for example Brandolini and Smeeding, 2009; or Raitano, 2016 ([41])). A second use of these decompositions has been to ascertain changes over time in the inequality contribution from different income sources. Jenkins (1995) uses this method at national level to examine the impact of taxes and benefits on income inequality trends in the United Kingdom during 1971–1986. Garcia-Peñalosa and Orgiazzi (2013) carry out a comparative inequality decomposition using Luxembourg Income Study data for six western countries. Their analysis spans 35 years and shows how different trends in labour and capital inequality contributed to changes in their inequality contributions in the six countries considered. However, their analysis stops in 2004 and has only one country that overlaps with our analysis (Sweden).

Following this strand of research, we focus on the **percentage changes** in the source contributions. This is because the comparison between countries of the **levels** of source contributions is hindered by data limitations, as we describe in Section 3.3 However, it is possible to examine changes in the source contributions over time, with the caveat that their levels vary greatly between countries. Hence, we follow Jenkins (1995) and examine primarily the percentage changes in each source contribution, $s_k\%\Delta S_k$, in two periods: the crisis period (2008–2013) and the subsequent period of recovery (2013–2018). For example, if changes in the inequality contribution from labour incomes are higher in the first period than in the recovery because of labour market adjustments, we expect $s_k\%\Delta S_k$ to be larger in the first period than in the second period for most countries. Clearly, the change in the contribution of each income source $s_k\%\Delta S_k$ must be interpreted in the light of its size (source share over total income) and the initial level of its proportional contribution s_k. Thus, we describe trends in the impacts of different income sources (whether these impacts are equalising or disequalising) by also presenting the corresponding shares for the years considered (2008, 2013 and 2018). Finally, for the sake of presentation in Section 3.4, we consider only changes in $s_k\%\Delta S_k$ greater than 1 % significant.

3.3. Income data: limitations of the inequality decomposition using EU-SILC

Our inequality decomposition is based on three cross-sectional files: 2008, 2013 and 2018 ([42]). Thus, we distinguish two periods in the analysis: 2008–2013 as the crisis period and its immediate aftermath, and 2013–2018 as the subsequent recovery ([43]).

We classify market and welfare-income sources in Table 3.1, and we break down household disposable income inequality by the income sources ([44]).

([41]) Raitano (2016) uses a comparative inequality decomposition during the 2008–2011 crisis with EU-SILC data. He shows the increasing role of earnings and self-employment in shaping inequality in the EU by reporting the **levels** of the inequality contributions from these income sources.

([42]) EU-SILC data reflect incomes in the previous year (except for Ireland, where incomes refer to the last 12 months before the interview period). The survey years have been used in this chapter; for example, 2016 refers to 2015 income components. The United Kingdom is not included.

([43]) This broad definition of crisis and recovery in two 5-year periods follows closely that of the European Commission (2020, pp. 88–94). However, country-specific episodes of economic crisis and recovery took place in different years.

([44]) The household income sources we use in the decomposition are equivalised at the individual level. Observations with disposable income above the 99.5th percentile of the national disposable income distribution have been removed because the inequality index decomposed (i.e. coefficient of variation) is highly sensitive to top incomes.

Public pensions are marked with * because of their mixed character ([45]). Other benefits include individual benefits (such as sickness benefits, disability benefits and educational allowances) and household-level benefits (such as family allowances, household allowances, housing benefits and benefits to prevent social exclusion not elsewhere classified). Finally, taxes include both personal income taxes and taxes on wealth.

The income decomposition in a comparative analysis is limited by the degree of comparability of some of the specific income sources across EU countries. In this respect, a recent study (Zardo-Trindade and Goedemé, 2020) has investigated and discussed the limitations affecting comparability across countries and over time. In an inequality decomposition by source, the sum of the proportional source contributions adds up to 1: if one source is under-reported, this will result in (1) a likely underestimation of its true contribution and (2) part of its (true) contribution being imputed to other sources ([46]). This hinders the comparison between countries because some income sources might be more likely to be under-reported in survey countries than in register countries. However, if under-reporting a source is assumed to be time constant ([47]), in a way that does not alter the relative proportions of the other source contributions, it is possible to examine the within-country percentage changes of the source contributions. As a result of this, two main limitations arise in the cross-country inequality decomposition with EU-SILC: (1) the reliability of capital income and (2) the availability of income values recorded net or gross for the different income sources.

With respect to reliability, when income data are derived from social security and tax records (as opposed to surveys), capital income is generally more reliable (Törmälehto et al., 2017). In France for instance, the collection of real-estate income data between 2007 and 2008 switched from surveys to registers, and this resulted in a doubling of the aggregate amounts of data collected (Burricand, 2013). Because the proportional inequality contributions of the different income sources add up to 1, if capital income is underdetected in surveys this is likely to result in the true proportional contribution of capital income being attributed to other income sources. This would partially blur the comparison of the disequalising effect of capital income with register countries, where the inequality contribution from capital income is better assessed. However, although the comparability of the shares and the source contributions across countries would be unreliable, percentage changes over time are more comparable. Percentage changes over time only require the assumption that the data collection procedure and potential biases did not change for the specific country in the period considered ([48]). Furthermore, to be on the safe side, we analyse changes in the disequalising effect of capital income for only the register countries.

Concerning availability of income values recorded net or gross for the different income sources, we would ideally want to assess the inequality contribution of different income sources that constitute disposable income from the perspective of the recipient. It may be argued that, from the wage-earner perspective, the most familiar wage concept is wages after the payment of employee social contributions but before personal income tax ([49]). This aggregate is not available in EU-SILC. Therefore, we are content to use the income sources recorded gross of the personal income tax and social contributions paid by the employee, for all countries in all years considered ([50]). Two cases are worth discuss-

([45]) Pensions in contributory pension systems may be thought of as deferred earnings and are therefore associated with market income. Conversely, pension systems that include minimum pensions are more associated with welfare benefit transfers.

([46]) Here, we assume that an under-reported source would result in a lower source contribution, but it clearly depends on which households tend to under-report it, and where those households are more likely to be concentrated in the disposable income distribution.

([47]) It is a reasonable assumption if under-reporting is due to data derived from surveys as opposed to registers. Conversely, for countries experiencing a transition to register income data, this assumption does not hold and within-country comparability over time would not be recommended.

([48]) Countries for which the data source changed from survey to register are Spain, Latvia (both from 2012 to 2013) and Austria (from 2011 to 2012).

([49]) Personal income tax is usually a single yearly payment that takes into account all household taxable income. It is therefore more intuitive for a wage earner to declare wages net of social contributions but gross of personal income tax.

([50]) Gross income sources are reported in the UDB as income variables ending in '_G'. We are not interested in the variables recorded net of personal income taxes, because this impairs analysis of the equalising impact of taxes on disposable income if the taxes were already deduced from the different income sources.

Table 3.1: Classification of market income sources and welfare income sources

Income sources in EU-SILC	Income sources	
+ Employee cash or near-cash income	Earnings	Market
+ Company car		
+ Cash benefits or losses from self-employment	Self-employment income	
+ Income from rental of a property or land	Capital income	
+ Interests, dividends, profit from capital investments		
+ Pensions received from individual private plans	Private pensions	
+ Old age benefits	Public pensions (*)	
+ Survivor benefits		
+ Unemployment benefits	Unemployment benefits	Welfare (taxes and transfers)
+ Sickness benefits	Household and individual benefits	
+ Disability benefits		
+ Education-related allowances		
+ Family-/children-related allowances		
+ Social exclusion not elsewhere classified		
+ Housing allowances		
+ Income received by people aged under 16		
+ Regular inter-household cash transfers received		
– Regular inter-household cash transfer paid		
– Regular taxes on wealth	Taxes	
– Tax on income and social insurance contributions		
= Total disposable household income		

ing: (1) the presence of social contributions within the wage and self-employment income concept in EU-SILC; and (2) the collection of benefits net of taxes in some countries. In the former, social contributions might impair the analysis of the disequalising contribution of wages, as the size of social contributions is very different across countries. In some Member States (e.g. Belgium), the share of social contributions paid by employees or the self-employed is much more significant than in others (e.g. Bulgaria). It is likely that both the share and the inequality contribution of earnings would be greater in countries with a very high incidence of labour taxation when including social contributions paid by employees ([51]). Benefits might be subject to personal income taxation (for example, this is the case in some Nordic countries – see Chapter 7 of this volume), so both shares and inequality contributions of benefits would be larger (at the expense of the share and contribution of taxes). Because of this, we believe that an important avenue for research is to use EUROMOD to correctly impute to each individual their earnings net of social contributions, and their benefits net of taxes.

However, it is still feasible to examine the **changes** over time of the equalising and disequalising roles of different sources, with some interpretation caveats. To be reliably analysed over time, for labour income and benefits requires the assumption that the tax policy for social contributions and benefit taxation did not change for the specific country in the period considered ([52]). Changes over time in both the share of the specific income source

([51]) If wages are reported gross of employee social security contributions, their contribution to inequality is likely to appear higher. Much depends on whether or not the social contributions are proportional to the wage (or self-employment income) level, as is the case in Belgium. Some countries also report net wages (EU-SILC variable PY010N), but this impairs the analysis of the role of taxes as in the footnote above.

([52]) It is a stronger assumption than for capital income (change in the collection technique). Part of the percentage change in the inequality contribution might be simply due to a reform of the social contribution schemes. Thus, a further avenue for research would be to remove social contributions from earnings, to carry out the inequality decomposition on these new 'corrected' sources.

k and its inequality contribution in the second period should be interpreted with the caveat that there were breaks in series for Sweden in 2015 and for Bulgaria, Luxembourg and the Netherlands in 2016 ([53]).

Finally, we do not present changes in inequality contributions from social transfers. This is because the equalising or disequalising role that social transfers play in disposable income cannot be definable *a priori*, unlike previous income sources presented in Table 3.1. Inequality contributions from social transfers are in some cases positive (suggesting that benefits have a disequalising effect) and in others negative (benefits have an equalising effect) ([54]). For this reason, unlike the other income sources, the change over time in the inequality contributions might imply a change in sign in addition to a change in magnitude ([55]).

3.4. Empirical evidence

Figure 3.1 presents to what extent the different income sources contribute to disposable income inequality in 2018 and their respective shares of disposable income ([56]).

Some general features of the different labour market and welfare regimes stand out, especially the equalising power of taxes in Nordic and continental EU countries as opposed to some eastern EU countries. However, the concerns about cross-country comparability argue against comparing the levels of the different sources' contribution, as highlighted in Section 3.3. Therefore, this section focuses on how the source contributions have changed over two periods: the crisis years (2008–2013) and the subsequent period of recovery (2013–2018). Figure 3.1 shows that the sign of the source contribution is intuitive for most income sources. The market income sources have a disequalising impact (i.e. they positively contribute to inequality in disposable incomes), while taxes have an equalising impact (i.e. they negatively contribute to inequality in disposable incomes).

Benefits do not have an intuitively obvious effect on disposable income inequality. Indeed, whether benefits have an equalising effect or a disequalising effect depends on how correlated they are with household disposable income. For instance, some sources such as unemployment benefits are linked with previous wage levels. Therefore, to the extent that individuals higher up in the disposable income distribution receive higher unemployment benefits, unemployment benefits have a disequalising effect ([57]). Likewise, public pensions, at least in contributory regimes, are generally positively correlated with disposable income, so their contribution is also disequalising. Another reason why unemployment benefits and public pensions are highly correlated with disposable household income is because of homogamy of households in terms of income and socioeconomic level.

([53]) The breaks relate to changes in the weighting method for Sweden; methodology and data collection with the introduction of six rotational groups for Bulgaria; data collection and weighting for the Netherlands.

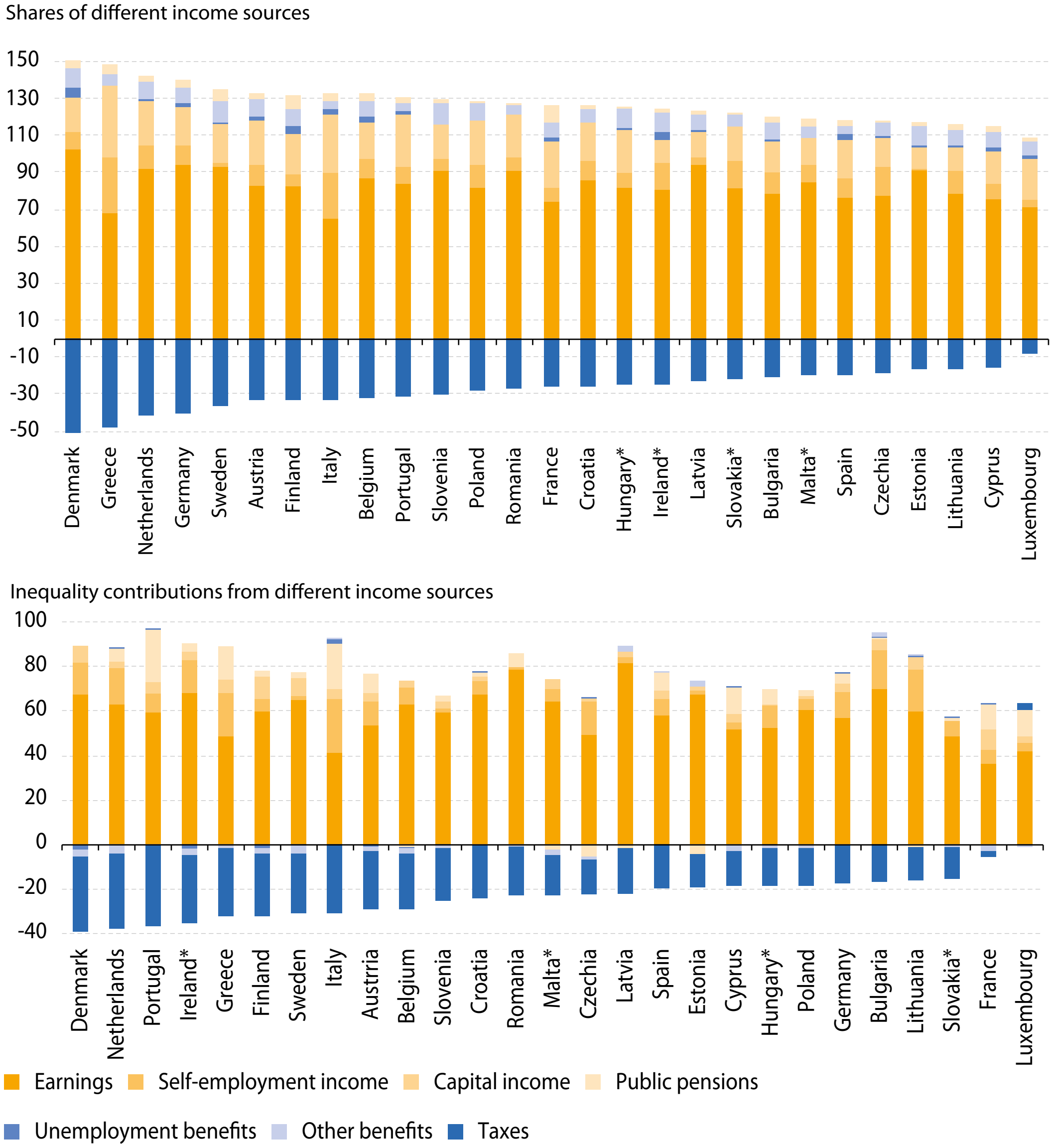
([54]) The social transfers considered are public pensions, unemployment benefits and any remaining benefits. These remaining benefits fall into two categories: (1) sickness benefits, disability benefits and educational allowances, which are attributed at individual level; and (2) family allowances, housing allowances and benefits to prevent social exclusion not classified elsewhere, all of which are recorded at household level. The inequality contributions from social benefits vary greatly across the EU. All types of social transfers have an equalising effect in Belgium and Denmark, while, for example, their role is consistently disequalising in Spain. Most EU countries have a more mixed picture that lies between these two extremes.

([55]) However, a table summarising the direction of the inequality contribution from social transfers across EU countries is available upon request.

([56]) Tables with point estimates of inequality contributions from each income source and their shares are available upon request to the authors (confidence intervals have also been calculated for the shares).

([57]) In fact, the primary social objective of unemployment benefits is insurance against unemployment and income replacement rather than mitigating inequality in disposable income.

Figure 3.1: Shares of income sources and their inequality contributions, 2018
(%)



Note: Data for Ireland, Hungary, Malta and Slovakia refer to 2017 instead of 2018. Breaks in series for Sweden (2015) and for Bulgaria, Luxembourg and the Netherlands (2016). Switch from survey to registers in Austria (2012) and in Latvia and Spain (2013).

Reading note: Shares of different income sources add up to 100 %. Absolute inequality contributions add up to the coefficient of variation.

Source: Authors' computations, UDB 2020-1.

3.4.1. Changes in the disequalising effect of labour income

This section analyses the changes in the disequalising effect of labour income. To identify explanations of the different trends over the two periods across the EU, we first document the trends in the labour income shares and then their correlation with their inequality contributions (Figure 3.2). The crisis period (2008–2013) was characterised by a general decrease in the shares of labour income due to a contraction of economic activity in a majority of EU countries. Conversely, the shares of labour income increased in the recovery period (2013–2018) following the economic expansion and improved labour market conditions in almost all EU countries (European Commission, 2020).

On the basis of this general trend (decreasing in the first period and increasing in the second), we may expect the following.

- A reduction in the disequalising contribution of labour income in the crisis period followed by a bounce back. This is the case when the reduction (increase) in the share is reflected in a proportional reduction (increase) in labour income along the household income distribution, leading to a more (less) compressed distribution.
- An increase in the disequalising contribution of labour income followed by a reduction. This is the case when the decline (increase) in the share is not reflected in a proportional reduction (increase) in labour income along the household income distribution. This might happen especially if the reduction in the share was due to less income from work for low- and middle-income households as a result of increasing unemployment or worsening employment conditions.
- Cases of reduction or increase in the inequality contribution of labour income in both periods.

Overall, the change in the labour income contribution depends on how the reduction (increase) in the share was distributed along the income distribution, signalling how differently less (more) income from work due to changing employment patterns affected households along the income distribution. In turn, these changes are the result of the underlying trends in wages and self-employment income, which do not necessarily move together. Indeed, when labour markets are in flux, one employment type might absorb potential unemployment from the other one. As earnings are the main components of disposable income across all EU countries, we expect the general trend in the disequalising trend of labour income to be driven mainly by the changes in shares of earnings and their inequality contributions ([58]). Indeed, earnings are the main source of disposable income across all Member States (Figure 3.1, first panel). Their shares of disposable income vary a lot across the EU, as they are lowest in countries such as Italy and Greece (65 % in Italy and 68 % in Greece in 2018), where a significant share of income is constituted by self-employment income. Conversely, income from self-employment represents a more modest share of disposable income than earnings, except in southern European countries, where it can make up as much as 25 % or more of disposable income (approximately 25 % in Italy and 30 % in Greece in 2018; Figure 3.1, first panel). However, the distribution of income from self-employment is known to be generally more unequal than the earnings distribution (Raitano, 2016). Thus, even relative small changes in the share of self-employment and its inequality contribution may drive significantly the

([58]) Between 2008 and 2018 the trend of earnings shares was V-shaped in 11 countries (Denmark, Latvia, Lithuania, Poland, Romania, Slovakia, Portugal, Spain, Hungary, Czechia and Greece), showing a slowdown of earnings in the aftermath of the 2008 crisis and a recovery after 2013 (see Figure 3.3, bottom panel). The Netherlands had an upstream reverse V-shaped trend. Earnings shares decreased in both periods in 3 countries (Estonia, Luxembourg and Finland), while in 6 other countries (Germany, Malta, Croatia, Ireland, Cyprus and France) earnings shares increased in both periods. For a handful of countries (Sweden, Slovenia, Belgium, Austria, Bulgaria and Italy) they were relatively stable between 2008 and 2018. Indeed, in the first period (the crisis years from 2008 to 2013), the correlation between the change in earnings shares and their inequality contribution is similar to the previous one for labour income (Pearson correlation coefficient = 0.65). Thus, a reduction in the earnings share is likely to lower their disequalising contribution. In the recovery period, characterised by an increase in the earnings share (2 % on average in the EU), the disequalising contribution from earnings did not change much overall. Evidence for this can be seen in the lower correlation between the changes in the shares (overall positive) and in their (rather stable) disequalising contributions (Pearson correlation coefficient = 0.33).

change in the final inequality contribution of labour income [59].

The correlation at country level between the percentage changes in the shares and in the inequality contributions from labour incomes is relatively high (Pearson correlation coefficient = 0.47 in the first period and 0.51 in the second period; Figure 3.2). Thus, in the first period a majority of countries displayed a reduction in the disequalising contribution and an increase in the second period. However, the clusters detectable according to the trends in the disequalising contribution of labour income are (Table 3.2):

- reduction in 2008–2013 and increase in 2013–2018;
- increase in 2008–2013 and reduction in 2013–2018;
- reduction in both 2008–2013 and 2013–214;
- increase in both 2008–2013 and 2013–214.

The first cluster includes Bulgaria, Hungary, Romania and Slovakia. The labour income contribution declined in the crisis years and then bounced back, in line with the first hypothesis, that the reduction (increase) in the share was reflected in a proportional reduction (increase) of labour incomes along the income distribution. Thus, in times of reduced labour income shares in the crisis years due to a contraction in employment, the correlation between labour income and household disposable income decreased. Conversely, in the recovery years, these eastern countries had their general trend driven by earnings (Romania, Slovakia and Hungary) except for Bulgaria, where the inequality contribution from self-employment income had a major role. All in all, in these countries the business cycle and its associated employment trend drove the trend in both shares and inequality contributions from labour income, as the change in them is proportionally reflected along the disposable income distribution.

The second cluster is composed of Germany, Estonia, France, Italy and Slovenia. In these countries, we document an inverse trend with respect to the first cluster, as the disequalising contribution increased in the crisis years and then declined in the recovery. That was due to different trends in the shares of labour income in some countries (they increased in Germany and France) or to an increasing disequalising contribution of earnings (Slovenia and Estonia to a lesser extent) in the first period. Conversely, in the second period the inequality contribution from labour income declined as a result of reducing inequality contributions from earnings in Estonia, Slovenia and Germany and from self-employment income in Italy and France.

The third cluster is composed of Greece, Lithuania, Luxembourg, Austria, Poland and Portugal. In these countries the disequalising contribution from labour income declined in both periods, driven mostly by earnings, but also by self-employment income in Greece (both periods), Portugal (first period) and Poland (second period). Overall, in this cluster the reduction in the disequalising contribution was driven by a reduced labour income share in the first period, whereas in the second period it was driven by the employment dynamics, whereby increasing earnings shares seemingly benefited low-income households to reduce the disequalising contribution of labour income overall. In the first and third clusters, the considerable reduction in the disequalising effect of labour income in many EU countries in the crisis years might possibly be related to the increase in unemployment among low-wage workers and the most vulnerable self-employed workers [60].

([59]) In the crisis years of 2008–2013, the share of self-employment income – and its disequalising contribution – dropped in many EU countries (see Figure 3.4 bottom panel). This is attested by the high correlation between changes in the self-employment income shares and in their disequalising contribution (Pearson correlation coefficient = 0.58). Only in three countries (Slovakia, France and the Netherlands) did the self-employment income share increase while its disequalising contribution declined. The increase in the share from self-employment income coupled with a reduction in its disequalising contribution might reflect a more compressed self-employment income distribution due to (1) increasing numbers of middle-income self-employed people or (2) generally higher self-employment incomes for low-income self-employed people. As the number of self-employment recipients in these three countries increased, the best guess is probably the former: increasing numbers of middle-income self-employed people.

([60]) The temporary loss of employment for some workers and/or self-employed people may have removed low earnings and self-employed incomes from the distributions in question. However, examination of the number of recipients for both income sources shows that it is not always the case that a reduction in the number of labour income recipients leads to a reduction in the disequalising contribution from labour income. The number of earnings recipients over time is available upon request.

The fourth cluster includes Ireland, Cyprus and the Netherlands. This cluster displayed an increasing disequalising contribution of labour income in both periods, mostly due to earnings or self-employment income in Ireland (second period). In Cyprus and the Netherlands, the increase in the inequality contribution is not linked to the corresponding decline in labour income share in the first period, signalling that the labour income distribution became more unequal in the first period, despite the reduction in its share.

Finally, a group of eight countries (Belgium, Czechia, Denmark, Spain, Latvia, Malta, Finland and Sweden) cannot be assigned to any of the four clusters, as changes in the inequality contribution from labour income were not significant in one or both periods.

This evidence shows significant between-country variation in changes in both the shares and the disequalising contributions from labour income. This confirms that the underlying processes determining inequality in disposable income due to labour market forces are highly variable both across countries and over time. More generally, the impact of labour market inequality on the overall distribution of disposable income should be examined in its interaction between self-employment income and earnings, as the two income sources do not always move in the same direction. Although earnings play a key role, because they form larger shares of disposable income, the disequalising role of self-employment played a role in a number of countries in determining the changes in the inequality contribution from labour income (e.g. Bulgaria and Portugal). This might be especially important in the light of the proliferation of self-employment in recent years and the increasing share of platform workers in this employment type (European Commission, 2018).

Table 3.2: Changes in the inequality contribution of labour income and contribution of earnings and self-employment income to these changes, clusters of countries, 2008–2013 and 2013–2018

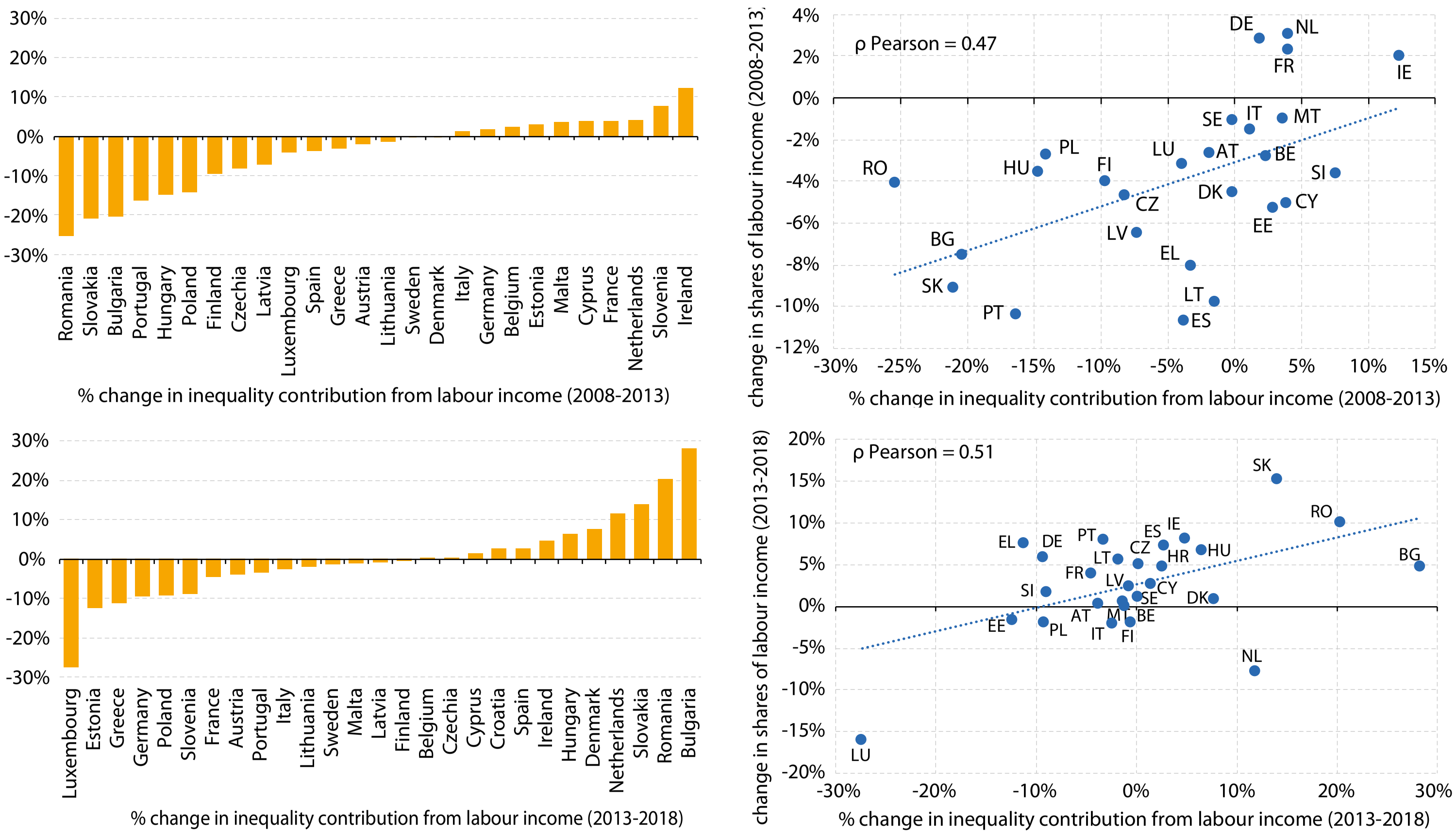
Labour income		Earnings	Self-employment
2008–2013 decrease; 2013–2018 increase	Bulgaria		✓
	Hungary	✓	
	Romania	✓	
	Slovakia	✓	✓
2008–2013 increase; 2013–2018 decrease	Germany	✓	
	Estonia	✓	
	France	✓	✓
	Italy	✓	✓
	Slovenia	✓	
2008–2013 decrease; 2013–2018 decrease	Greece	✓	✓
	Lithuania	✓	
	Luxembourg	✓	
	Austria	✓	
	Poland	✓	✓
	Portugal	✓	✓
2008–2013 increase; 2013–2018 increase	Ireland	✓	✓
	Cyprus	✓	
	Netherlands	✓	

Note: Data for Ireland, Hungary, Malta and Slovakia refer to 2017 instead of 2018. No data for Croatia for 2008-2013.

Reading note: The first cluster includes Bulgaria, Hungary, Romania and Slovakia. The labour income contribution declined in the crisis years and then increased between 2013 and 2018.

Source: Authors' computations, UDB 2020-1.

Figure 3.2: Change in inequality contribution from labour income (left-hand side) and its correlation with change in share of labour income (right-hand side), 2008–2013 and 2013–2018
(%)

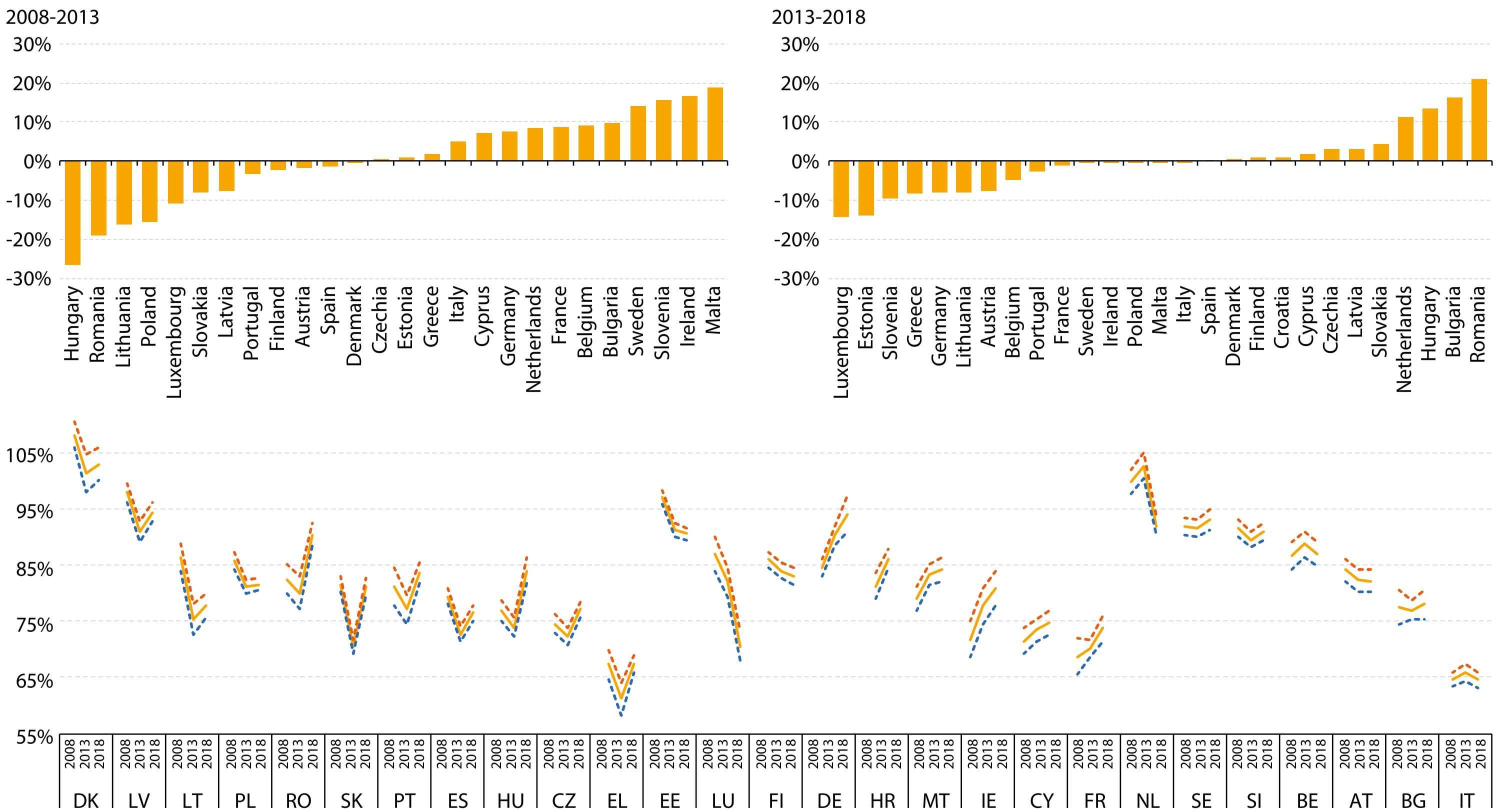


Note: See Appendix 2 for a list of country abbreviations. Data for Ireland, Hungary, Malta and Slovakia refer to 2017 instead of 2018. Breaks in series for Sweden (2015) and for Bulgaria, Luxembourg and the Netherlands (2016). Switch from survey to registers in Austria (2012) and in Latvia and Spain (2013). No data for Croatia for 2008-2013.

Reading note: Negative (positive) changes in inequality contribution indicate that labour income became less (more) disequalising. Negative (positive) changes in shares indicate that labour income share decreased (increased).

Source: Authors' computations, UDB 2020-1.

Figure 3.3: Change in inequality contribution from earnings (upper panels) and evolution of the shares of earnings on disposable income (bottom panel), 2008–2013 and 2013–2018
(%)

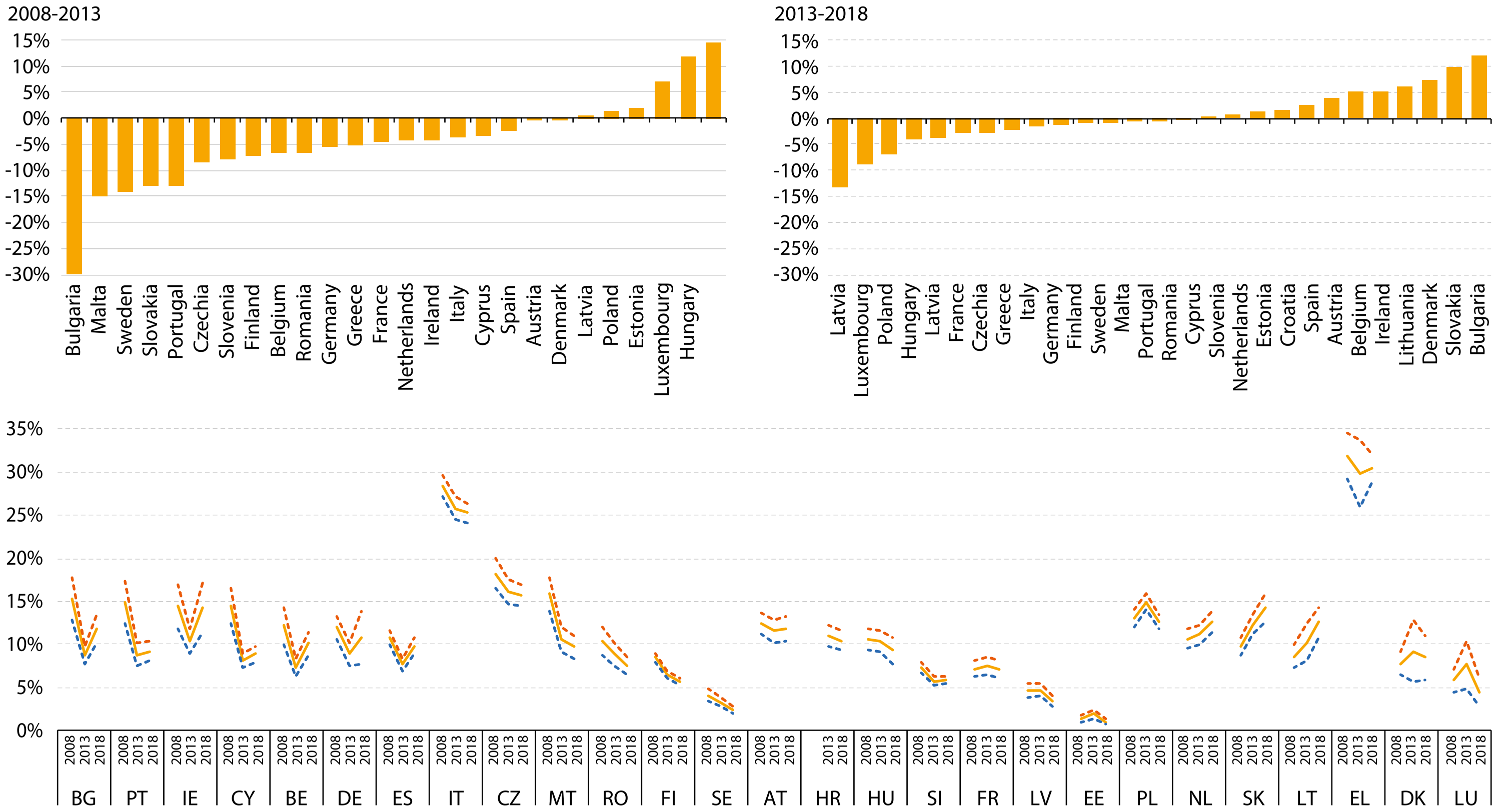


Note: See Appendix 2 for a list of country abbreviations. Data for Ireland, Hungary, Malta and Slovakia refer to 2017 instead of 2018. Breaks in series for Sweden (2015) and for Bulgaria, Luxembourg and the Netherlands (2016). Switch from survey to registers in Austria (2012) and in Latvia and Spain (2013). No data for Croatia for 2008-2013.

Reading note: Negative (positive) changes in inequality contribution indicate that labour income became less (more) disequalising. Regarding the shares, yellow lines indicate point estimates, while blue and red lines indicate respectively the lower and upper bounds of the confidence interval.

Source: Authors' computations, UDB 2020-1.

Figure 3.4: Change in inequality contribution from self-employment income (upper panels) and evolution of the shares of self-employment income on disposable income (bottom panel), 2008–2013 and 2013–2018
(%)



Note: See Appendix 2 for a list of country abbreviations. Data for Hungary, Ireland, Malta and Slovakia refer to 2017 instead of 2018. Breaks in series for Sweden (2015) and for Bulgaria, Luxembourg and Netherlands (2016). Switch from survey to registers in Austria (2012), Latvia and Spain (2013). No data for Croatia for 2008-2013.

Reading note: Negative (positive) changes in inequality contribution indicates that self-employment income became less (more) disequalising. Regarding the shares, yellow lines indicate point estimates, while blue and red lines indicate respectively the lower and the upper bound of the confidence interval.

Source: Authors' computations, UDB 2020-1.

3.4.2. Changes in the disequalising effect of capital income

Income from capital is known to be an extremely concentrated income source. EU-SILC includes income from rental of property or land; interest; and profits or dividends from a business investment ([61]). Previous evidence points to a general drop in capital income at EU level, especially investment income, as a result of the crisis (Jenkins et al., 2012). Thus, we expect that the disequalising effect of capital income declines in the immediate aftermath of the crisis.

This is because capital income is particularly concentrated at the top of the income distribution, so it is likely that a reduction in its share, especially if not income from housing rents, would result in higher income losses for high-income households. Owing to data limitations discussed in Section 3.3, we present the changes in the disequalising effect of capital for only countries that derive capital income from register sources. The trend in the share of capital income shows a general reduction for all countries in the first period, except Slovenia (Figure 3.5). This effect is likely to depend on the decline in income distributed from corporations (dividends). In turn, the capital income share recovered in the Nordic countries while it kept declining for Spain, France and the Netherlands in the second period. The change in the disequalising contribution of capital follows relatively closely the trend in its share of disposable income. Indeed, in Spain, France and the Netherlands, the disequalising contribution of capital income reduced significantly in both periods, while in the Nordic countries it first reduced and then increased in the recovery period ([62]). Behind an increase in the capital contribution to inequality may lie an increase in the rate of return of capital or more favourable capital taxation. However, investigation of these factors is beyond the scope of this chapter.

([61]) The disposable income concept in EU-SILC does not include imputed rents or the retained earnings of corporations. Thus, capital income in Section 3.1.1 is not supposed to match the definition in national accounts.

([62]) García-Peñalosa and Orgiazzi (2013) find a rather reduced disequalising role for capital income in Sweden until 2004 with Luxembourg Income Study data.

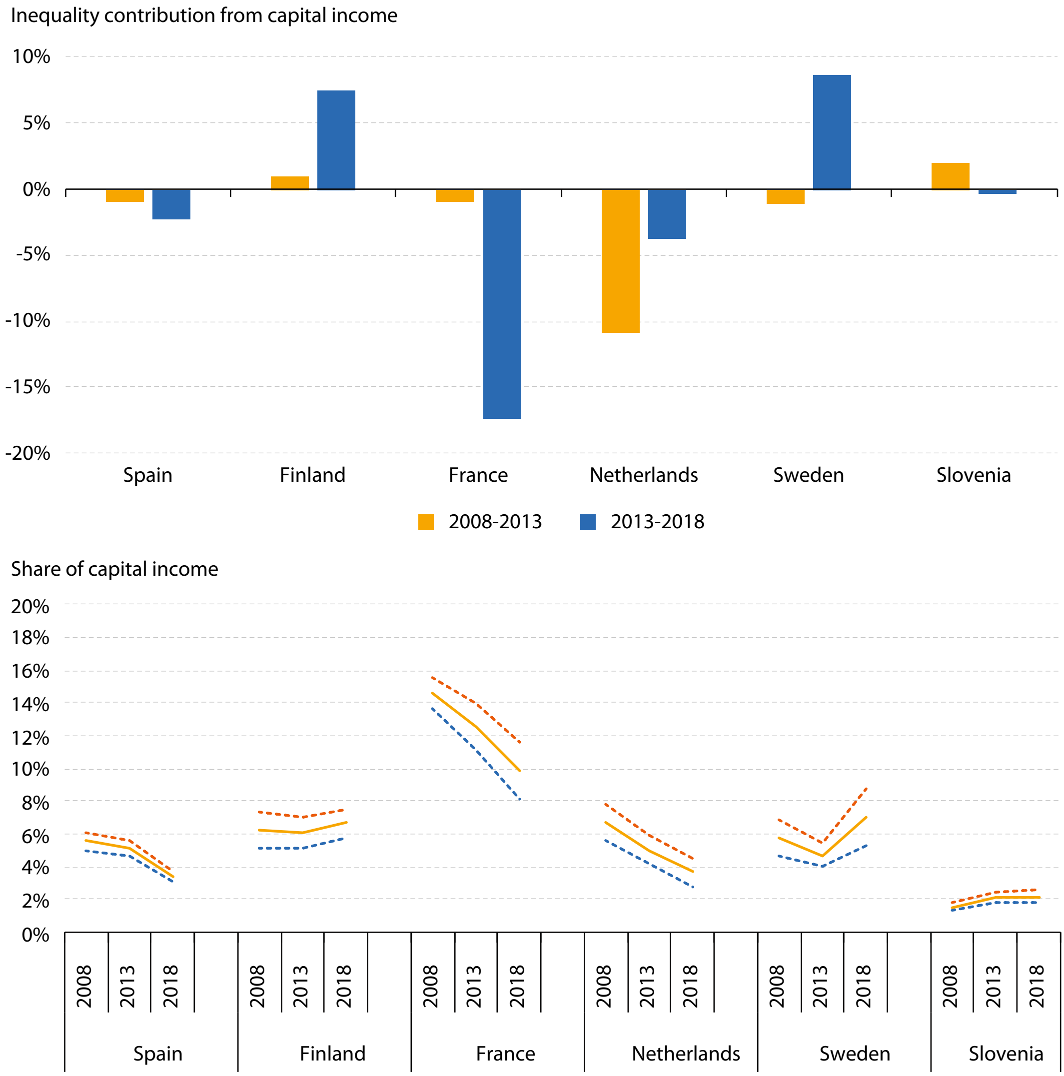
3.4.3. Changes in the equalising effect of taxes

We expect that the shares of taxes increase in the countries that are subject to fiscal consolidation or, as automatic stabilisers, in periods of economic expansion. In this regard, it is highly likely that the tax share moves to some extent in the same direction as the shares of labour income; in other words, the more the share of labour income increases, the more taxes on income are likely to be paid. However, the change in the inequality contribution ultimately depends on the progressiveness of the tax system. An increase in the share of taxes might trigger a rise in the equalising power of taxes, if it is highly progressive, to affect mostly high-income households. Conversely, if the increase in the share of taxes is distributed to reduce the inverse correlation with household disposable income, its equalising impact may decline. The crisis years were characterised by a slight decrease in the tax share, depending on their role as automatic stabilisers in the aftermath of the crisis. This trend appears highly correlated with the deterioration of the equalising role of taxes reported over the same period (Pearson correlation coefficient = –0.78). Conversely, the share of taxes increased in the same period, as the recovery kicked in in all EU countries. However large, the correlation between the change in the tax share and its equalising contribution decreased in this period (Pearson correlation coefficient = –0.57). The equalising effect of taxes slightly decreased (on average) in both periods, and even more between 2013 and 2018 (Figure 3.6; positive (negative) bars indicate deterioration (improvement) in the equalising role of taxes). Thus, the clusters of countries that can be traced for these changes overlap to some extent with those for the changes in the disequalising contribution from labour income.

A cluster of countries where the equalising contribution of taxes decreased in the first and then rose in the second period is composed of the same eastern countries as in Table 3.2 plus Finland and Denmark. Likewise, a cluster of countries where the equalising role of taxes rose in the crisis years, to then deteriorate later on, includes Germany, France and Slovenia, where the disequalising contribution of labour income followed the same pattern as the

Figure 3.5: Change in inequality contribution from capital income (upper panel) and in the shares of capital income in disposable income (bottom panel), 2008–2013 and 2013–2018

(%)



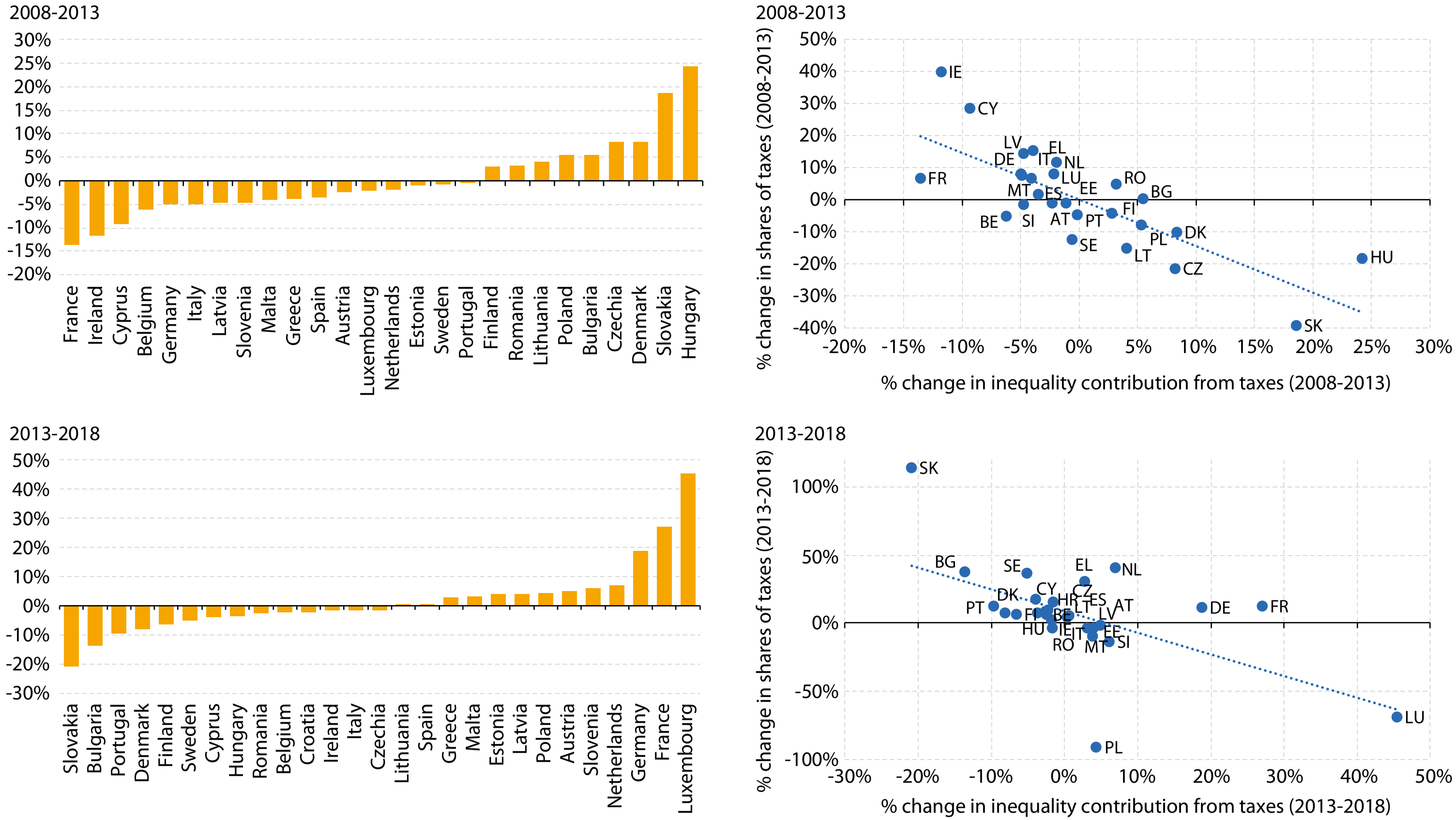
Note: Spain switched in 2012 to administrative data.

Reading note: Negative (positive) changes in inequality contribution indicate that capital income became less (more) disequalising. Regarding the shares, yellow lines indicate point estimates, while blue and red lines indicate respectively the lower and upper bounds of the confidence interval.

Source: Authors' computations, UDB 2020-1.

second cluster in Table 3.2. Finally, in three countries the equalising role of taxes increased in both periods (Belgium, Ireland and Cyprus), while Poland is the only country where the equalising contribution from taxes declined in both periods. Therefore, for a correct assessment of inequality patterns for future purposes, it may be relevant to contrast the changing disequalising role of labour income with the equalising effect of taxes. In this way, it is possible to ascertain which effect prevailed to determine a particular inequality pattern. Countries where fiscal consolidation took place (Ireland, Greece, Spain, Italy, Portugal) had generally increasing equalising roles played by taxes. However, it is likely that the progressiveness of the tax system and its link to labour income trends mattered more than the general increase in tax revenues to determine the changing (almost always increasing) equalising role of taxes in these two periods.

Figure 3.6: Change in inequality contribution from taxes (left-hand side) and its correlation with change in shares (right-hand side), 2008–2013 and 2013–2018
(%)



Note: See Appendix 2 for a list of country abbreviations. Data for Ireland, Hungary, Malta and Slovakia refer to 2017 instead of 2018. Breaks in series for Sweden (2015) and for Bulgaria, Luxembourg and the Netherlands (2016). Switch from survey to registers in Austria (2012) and in Latvia and Spain (2013). No data for Croatia for 2008-2013.

Reading note: Negative (positive) changes in inequality contribution indicate that labour income became less (more) disequalising. Negative (positive) changes in shares indicate that labour income share decreased (increased).

Source: Authors' computations, UDB 2020-1.

3.5. Conclusions

Inequality decomposition by income source is a useful tool to assess changes in disposable income inequality. It gives information about (1) the role of labour and capital markets in shaping inequality and (2) the role of taxes and transfers in mitigating inequality. However, to be properly used in comparative analysis, the reliability of data on the different income sources should be equivalent across countries. In the light of the different degrees of data reliability for particular income sources (especially the differences between data derived from surveys and those from registers), a comparison across countries of the source contributions to inequality is not robust at this point. Further harmonisation of the data collection techniques, and increasing reliability of the different sets of data on income sources, will make possible a more extensive comparison between countries of the contributions made by different sources to inequality (and their corresponding shares of disposable income). However, it is still possible to make a preliminary analysis of the changes in the source contributions to disposable income inequality over time. Because labour income and capital income present disequalising contributions to inequality – while taxes have an equalising effect – we examine the percentage change of their contribution over time.

The findings of such a decomposition show that labour income's disequalising contribution to inequality varied greatly across EU countries in the crisis years (2008–2013) and in the subsequent period of recovery (2013–2018). In the crisis years, labour income share and its disequalising contribution to inequality declined in most EU countries, while it increased on average in the recovery years. Overall, the pattern of change was very country-specific and often varied at country level between the two periods. This makes it difficult to draw general, EU-wide conclusions on the trend in labour income's disequalising impact. Moreover, owing to its highly disequalising contribution, the role of self-employment income was relevant in driving the disequalising contribution of labour income in a number of countries. This therefore seems to point to (1) dissimilar country trends in the disequalising contribution of labour income and (2) potentially dissimilar dynamics between labour income's two components: earnings and self-employment income.

The inequality contribution from capital income observed in register countries (countries where data are derived from registers such as tax records) shows (1) a reduction in its disequalising effect in both periods in Spain, France and the Netherlands and (2) a reduction followed by an increase in its disequalising effect in the recovery period in Finland and Sweden.

Welfare sources such as public pensions and benefits are not assessed in terms of their change over time because the sign of their inequality contribution is not straightforwardly negative or positive as it is for other income sources. The equalising contribution from taxes follows closely the trend of the (disequalising) contribution from labour income in the light of the expected role of taxes as automatic stabilisers whose share follows the business cycle.

All in all, these findings highlight the difficulty of ascertaining common patterns or causes underlying changes in inequality. The changing role of different market and welfare income sources (switching from equalising to disequalising and vice versa) are highly country-specific, time-specific and varied across EU countries. Finally, two potential avenues for improving the comparability of inequality contributions and shares of different income sources are (1) more reliable collection of capital income data and (2) the availability of earnings income and self-employment income net of social contributions paid by employees. The latter could benefit from the use of EUROMOD to impute to each individual their earnings net of social contributions, and their benefits net of taxes.

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4 Regional disparities during the Great Recession: an application of multiannual average approximation in six EU Member States

Matthias Till ([63])

4.1. Introduction

Social indicators are primarily used to monitor developments over time. They can become particularly useful if disaggregated, for example by characteristics such as gender and age (Atkinson et al., 2002). Studying where the poor live can also help increase the effectiveness of actions that aim to reduce poverty (see UNECE, 2020). Regional breakdowns are especially relevant to those policies that are regulated by regional or local authorities, such as housing, childcare and social assistance (Till et al., 2018).

The potential of EU-SILC for such spatial disaggregation should be exploited to the maximum possible degree. This chapter presents a regional disaggregation of the AROPE indicator in six countries ([64]): Czechia, Spain, Italy, France, Austria and Slovakia. Together, these countries have a population of 194 million inhabitants or roughly 43 % of the population of the current 27 Member States. As far as data are available, regional disaggregation in this chapter refers to NUTS 2 regions. The hierarchical NUTS nomenclature mirrors territorial administrative divisions within Member States. With between 800 000 and 3 million inhabitants, NUTS 2 regions are the primary focus of EU regional policies. Within the NUTS 2 regions of these six countries, this chapter also attempts to distinguish densely populated urban areas from non-urban areas ([65]).

As the statistical uncertainty of single-year estimates is relatively large, we employ average annual approximation (AAA) as a simple strategy to improve the precision of regional EU-SILC indicators by cumulating indicators over 3 or more years (Till et al., 2018). This method reduces standard errors by approximately 25 %. Most results presented in this chapter have standard errors below 2.5 percentage points (p.p.), corresponding to a confidence interval of roughly 5 p.p. around the point estimates.

The assessment presented in this chapter also addresses specifically if and how changes in regional distribution of poverty can be detected in EU-SILC data. Before the current COVID-19 crisis, the EU had just recovered from one of the most severe crises in peacetime economic history, the global financial crisis. Whether or not that dramatic event fundamentally changed spatial disparities is one of the central questions of this chapter.

The chapter is organised as follows: Section 4.2 discusses the motivation prompting better exploita-

([63]) Matthias Till is with Statistics Austria. The author gratefully acknowledges generous support from several colleagues. Technical assistance in R programming was provided by Johannes Gussenbauer (Statistics Austria). Josè Maria Mendez, Róbert Vlačuha and Boris Frankovič provided additional information on sampling and regional disaggregation in their countries; Nick Longford and Tim Goedemé were consulted on specific technical questions; comments on an earlier version of this paper were provided by Paola Annoni, Gianni Betti, Anne-Catherine Guio, Brian Nolan, Philippe Van Kerm, Dragana Mandic, Eric Marlier and Jean-Marc Museux. This work was supported by Net-SILC3, funded by Eurostat and coordinated by LISER. The European Commission bears no responsibility for the analyses and conclusions, which are solely those of the author. Email address for correspondence: Matthias.till@statistik.gv.at

([64]) Restricted access to regional information prohibits comprehensive coverage across all EU Member States. The selection of countries was determined by access to the required regional information.

([65]) Urban areas are here defined as municipalities (local administrative units) considered densely populated areas according to the degree of urbanisation (Degurba) classification. Those areas have a minimum population of 50 000 and are characterised by contiguous grid cells of 1 km2 that have a density of at least 1 500 inhabitants per km2.

tion of EU-SILC data for effective allocation of social investments. Section 4.3 describes the availability of regional information in the UDB. Section 4.4 presents the AAA method. Section 4.5 shows how the crisis years are reflected in the AROPE indicator at EU and national levels. Section 4.6 provides such information at regional level, while Section 4.7 illustrates regional disparities. Section 4.8 addresses the difficult question of the evolution of AROPE at regional level and Section 4.9 concludes.

4.2. The potential of indicators for effective allocation of social investments

One of the aims of the European Structural and Investment Funds (ESIF) is to support regions that need investment. The social investment package aims to promote economic stabilisers that stimulate long-term growth, notably by investing in children and their education (Frazer et al., 2014). The total investment from ESIF amounts to EUR 638 billion (2014–2020, including EU and national contributions) (66). The average annual EU budget for ESIF amounts to EUR 65 billion or close to half of the total EU budget. By comparison, global development aid amounts to roughly EUR 120 billion per year (67). ESIF contributions amount to more than 50 % of total public investment in several countries (Dijkstra, 2017, p. xxii).

Currently, some EU funds target regions with a low GDP per capita (European Commission, 2014). As a measure of goods and services produced in a certain region, GDP per capita may, however, not reflect the actual circumstances of persons living in this region, for example if the proportion of people who commute between regions is relatively large. Furthermore, the estimation of regional GDP may be subject to errors in measurement (68). For analytic purposes, the European Commission also monitors social dimensions in its regional Social Progress Index, which is available for all NUTS 2 regions (69) but excludes economic indicators such as those that measure poverty.

By contrast, in the United States, indicators derived from the American Community Survey (ACS) support the annual allocation of USD 675 billion in federal and state funds to the poorest regions. The ACS collects information on poverty from a massive sample comprising 2.2 million addresses interviewed per year (US Census Bureau, 2014).

Clearly, the EU has no instrument comparable to the ACS. With an effective minimum sampling size of only 135 000 households per year, EU-SILC is more similar to the Current Population Survey in the United States, which is mainly used for nationwide monitoring of changes in unemployment and poverty. Although the accuracy of EU-SILC at regional level is limited given these sample sizes, its potential for regional analysis is worth exploiting.

4.3. Regional information in the User Database

As had already been highlighted by Verma et al. (2010, p. 56) a decade ago, 'the production of indicators of poverty and social exclusion from EU-SILC at the level of sub-national regions is severely limited due to lack of information in the microdata on sample structure and for the identification of regions'.

In the context of this paper, availability, quality and comparability over time are crucial with regard to the following variables in the UDB:

- regional identifiers (DB040, DB100)
- strata identifiers (DB050; this variable has been removed completely from UDB data)
- primary sampling unit (PSU) identifiers (DB060)

(66) https://cohesiondata.ec.europa.eu/overview#
(67) http://www.oecd.org/dac/development-aid-rises-again-in-2016-but-flows-to-poorest-countries-dip.htm
(68) Although groups of regions are defined by their GDP per capita, the actual allocation of funds to projects in specific regions does consider other regional indicators than GDP.
(69) This index (https://ec.europa.eu/regional_policy/en/information/maps/social_progress) closely reflects the methodology of the Global Social Progress Index published by a non-profit enterprise in the United States (https://www.socialprogress.org/).

- person identifiers (RB030, available in linkable form only from 2015).

In principle, the UDB provides current NUTS ([70]) classifications (DB040). To further distinguish urban from non-urban areas, this can be combined with data on degree of urbanisation (DB100).

The UDB still does not, however, provide regional identifiers for all countries, or it refers to different levels of disaggregation, and special data requests need to be made to access regional information (see Table 4.1) ([71]).

Information on sample structure is essential to be able to properly assess the precision of regional estimates. However, the variable that identifies sampling strata (DB050) has been removed completely from UDB data. Moreover, the variable that identifies PSUs (DB060) is often missing and needs to be reconstructed making the best possible use of the information that is available (Goedemé, 2010; Zardo and Goedemé, 2016) ([72]). For a substantial number of cases in France and Italy, the household identifier had to be assumed as the PSU as a simplification. This is unfortunate because the precision obtained from a sample of households can be substantially reduced if these households were selected in a second stage after a much smaller number of municipalities was selected, for example. Occasionally, 'lonely' PSUs occur, which have no other PSU in their (assumed) stratum, or PSUs appear in more than one stratum ([73]). Computational strata needed to be created on an ad hoc basis to obtain a sample design structure that could be used in practice.

When estimates are cumulated over time to improve sampling precision, it is essential to consider the overlapping design of a longitudinal panel survey. In this situation, the precision gain from cumulation is considerably lower than when estimates from independent cross-sectional samples were combined (Till et al., 2018). A replication method such as bootstrapping must make sure that the same sampling units are included with identical weights in all waves for which the unit was eligible. This implies that identification numbers need to be linkable across waves. In the UDB, that is generally the case for all countries after the 2015 EU-SILC iteration. The absence of longitudinal identifiers before 2015 implies that the variance of cumulated estimates is underestimated for earlier years.

The partly reconstructed sample design information was used to produce 500 replicate weights for each data set, which allowed variance to be estimated (Till et al., 2018).

Statistical offices usually adjust weights (calibration) in sample surveys to establish the coherence of certain distributions with the official population structure. The replicate weights therefore also need to be calibrated. In this exercise they were adjusted to match the distribution of household size, sex and 15-year age groups in the full sample. Statistics Slovakia provided special regional data; however, it could not be merged with the UDB, and only household size could be used for calibration for this country. The actual calibration models are likely to consider a larger number of control variables. Actual standard errors may therefore be overestimated, depending on how strongly these control variables are correlated with the poverty variable ([74]).

Given the importance of sampling precision for regional disaggregation, the approximations described above are not a fully satisfactory solution. The absence of reliable sample design information

([70]) NUTS classifications are kept stable for a minimum of 3 years before they are updated for occasional changes in administrative regions. These updates seem to be reflected with some further time lag in the EU-SILC data. It is difficult for users to trace these changes, and they may experience difficulties when names of regions are changed.

([71]) The author gratefully acknowledges support from Róbert Vlačuha (Slovakia) and José María Méndez Martín (Spain), who provided additional information.

([72]) The sample design variables (strata1 and psu1) contained in the comma-separated values files provided by Tim Goedemé were matched to the UDB data. With the help of SPSS code provided by Herter and Wirth (2018), the sample structure for 2018 could be reconstructed using the same rules (see https://timgoedeme.com/eu-silc-standard-errors/).

([73]) Such a situation arises if, for example, the code of either strata or PSU refer not to the original sample but perhaps to the region in which the household is located at the time of the interview. Sometimes codes or sampling designs have changed over time so that with a longitudinal design it becomes impossible to verify the correct sample structure.

([74]) It ought to be noted that in most countries calibrated weights restore only control distributions at national level. These controls may not be equally appropriate for every region. However, cross-sectional weights are to be preferred over uncalibrated design weights, to maximise consistency with national aggregates. If control distributions (e.g. with regard to household size) are known to differ systematically across regions, precision could be improved by systematically using this information for calibration (see Ardilly, 2015).

Table 4.1: Availability of regional identifiers in UDB data (EU Member States)

Identifiers	UDB providing data for these countries
DB040 and DB100	CZ, ES, FI, FR
Only NUTS 1 data	AT, BE, BG, EL, HU, IT, PL, RO, SE
No regional disaggregation	CY, DK, EE, HR, LT, LU, LV, MT, NL, PT, SI, SK
No data in UDB (release 2018-2)	DE, IE

Note: See Appendix 2 for a list of country abbreviations. In the 2018 data, new NUTS codes were introduced for France and Poland reflecting the NUTS 2016 revision. For the purposes of this chapter, additional variables were provided by Austria and Slovakia. Statistics Slovakia provided NUTS 3-level identifiers after 2015 (without information on the degree of urbanisation).

remains a serious concern, as do unavoidable simplifications and possible sources of error.

The cumulated sample of 6 countries and 11 years (2008–2018) included in this analysis contains almost 1.7 million records (75).

4.4. Improving precision of EU-SILC estimates by average annual approximation

Strategies for possible improvements of sampling precision of EU-SILC for regional analysis may be broadly distinguished as follows (Verma et al., 2017, p. 176):

- adjusting the size, allocation or design of regional samples;
- estimation techniques that use auxiliary information;
- simplification by aggregation of information over space, time or indicators.

The first of these strategies is reflected in the regional precision requirements specified in the framework regulation for social statistics. Compared with the policy need for regional disaggregation, however, these requirements are modest. It is clear that the necessary changes in data collection imply considerable cost and time for implementation.

The second strategy is addressed by small area estimation, which has been developed as an alternative (or complementary) strategy to changes in sample design (Tzavidis et al., 2016). Those approaches are highly sensitive to the model specification. Each approach may yield different results, precision gains and potential bias. Methods may target units or areas. The methodological choices can be challenging for users and may lead to problems with strategic decisions based on small area estimation. The World Bank (Qinghua and Lanjouw, 2009) has developed a model-based approach, which is widely used. It combines sample data and census information to obtain poverty maps. Such model-based methods can provide estimates even for extremely small territories for which no sample observations may be available. If the number of observations is sufficient, enhanced calibration, which uses auxiliary information at regional level, is a possible alternative (Ardilly, 2015). Regional calibration avoids the bias of model-based estimates and has potential for the regular production of EU-SILC.

The approach proposed in this chapter belongs to the third strategy. It may be understood as approximation, as it simply replaces a specific estimate with a more robust estimate that is considered sufficiently similar. As an extreme example, one could use only the level of aggregation for which data are reliable, assuming that the value for a large region is a valid approximation for all the areas within that region. Indeed, cohesion policies mainly address NUTS 2 regions because there are very few comparative data below that level. However, in most Member States this nomenclature will not reflect corresponding authorities. Disparities within these

(75) To facilitate the further analysis, a small number of records were eliminated. A few records ($n = 79$) had a missing value for the DB040 variable. In addition, three rare combinations of Degurba (DB100) and NUTS 2 (DB040) regions were eliminated ($n = 44$). These relate to records in AT11 (Burgenland) and FRM0 (Corsica), which were classified as urban, and CZ01 (Prague), which was identified as intermediate.

regions may, however, be sizeable, for example between cities and less densely populated areas.

A similar variant would be to consolidate estimates in a kind of social index over different but reasonably similar indicators, for example the AROP rate with different income thresholds. This can eventually improve precision but comes at the cost of losing clarity of definition (Verma et al., 2010). Similarly, the approach can benefit the construction of multidimensional indicators (Weziak-Bialowolska and Dijkstra, 2014).

In this chapter, regional estimates are cumulated over time. For example, in this method an indicator may be obtained by taking the average of estimates for 3 successive years in the same region. If structural patterns can be assumed to be reasonably robust over time, the implied loss of accuracy will be acceptable. The cumulation may consider any number of consecutive years. Normally, this approach is used to cumulate across the same set of years. For example, if the objective were to demonstrate persisting challenges in a region or city, cumulation over a decade might be appropriate. The underlying assumption is that no changes occurred. In the context of a crisis, it may be more appropriate to cumulate over fewer and more recent data points. Short-term shocks, which may occur at different times and magnitude in different regions, may of course imply some sensitivity. However, the procedure can be assumed to be robust to more significant transformations ([76]).

The cumulation refers to estimates, instead of pooling data at micro level ([77]). Those estimates are weighted equally. The cumulated estimate can thus be considered an estimate for the middle of the observation period, even if the sample size of adjacent years happens to be larger ([78]). To distinguish such simplified estimates with enhanced precision from single-year direct estimates, they are here referred to as AAA. The approach is particularly flexible and may in fact be applied to any estimate that is based on population subgroups with small sample sizes, such as certain groups of migrants or occupations. Furthermore, the approach can easily accommodate any type of indicator, including complex non-linear indicators such as the Gini coefficient. Its precision gain for NUTS 2-level estimates has been found to be similar to small area estimation (Bauer et al., 2013). Cumulation of estimates over time is simple to implement and can easily be understood and communicated. If, for example, the AROPE indicator for a certain region takes the values 23, 28 and 24 % in 3 successive years, the AAA estimate will be 23 + 28 + 24 = 75/3 = 25 %.

The assessment of sampling precision is the critical element of such an AAA estimate. With the R package *surveysd* (available from the Comprehensive R Archive Network), Statistics Austria has implemented a ready-to-use software algorithm to obtain not only point estimates but also standard errors, which consider sample overlaps between years ([79]).

4.5. How the crisis years are reflected in the at risk of poverty or social exclusion rate

The Great Recession is sometimes described as a sequence of three events. First, a financial crisis originated in the housing market in the United States in 2007–2008 and culminated in the collapse of Lehman Brothers. The second event is the recession that followed with only a short delay, in the final quarter of 2008 in most countries, and led to a sharp fall in economic output and employment in 2009–2012. In 2010, the European Stability

([76]) This assumption can be illustrated by analogy to the four seasons of a continental climate. Normally, a cumulation of temperature measurements over several days would suffice to safely distinguish winter from summer.
([77]) The relative advantages of aggregating estimates instead of pooling data at a micro level are discussed by Verma et al. (2017, p. 178). In particular, it is held that microdata pooling may not be feasible in all circumstances, for example if changes in sample design over time add too much complexity.
([78]) Alternatively, weights may be determined with regard to the distance from the centre point or in proportion to their variances, to improve efficiency. Assessment of sensitivity with regard to such refinements may be addressed in further research.
([79]) If samples were independent (including the selection of PSUs and strata), the margin of error would be reduced in proportion to the number of samples and could be calculated as the square root of the sum of variances for each year divided by the number of years. In the case of a rotational panel, however, there is a sample overlap, and a covariance term needs to be considered, which will reduce the precision gain from cumulation.

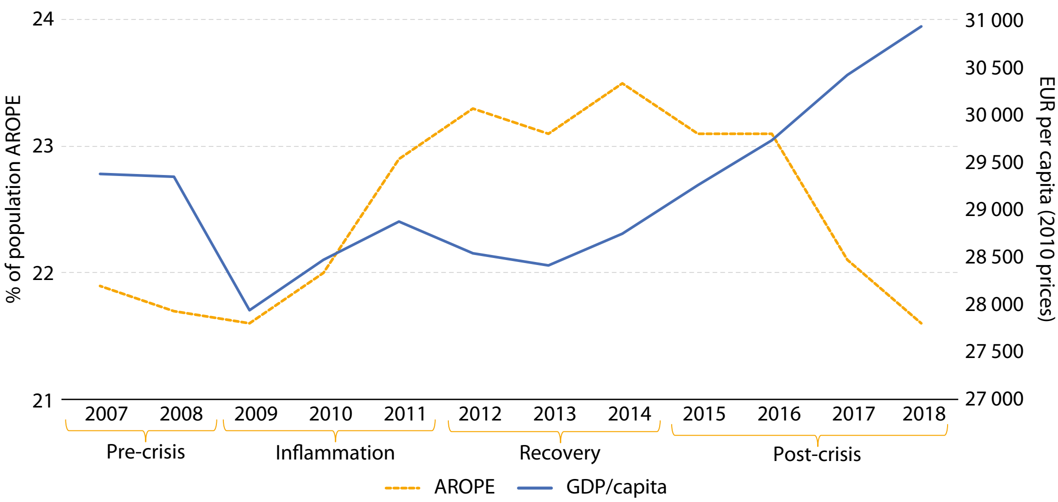
Mechanism was created to safeguard the euro area against the severe sovereign debt crisis in 2010–2014, which particularly hit Ireland, Greece, Spain, Cyprus and Portugal.

Because of the particular role of the common currency and the mitigation of the debt crisis through the European Stability Mechanism, it appears justified to distinguish between crisis developments in and outside the euro area. All countries considered in this chapter, except Czechia, are Member States of the euro area.

The different phases of this crisis are reflected in the development of real GDP per capita and the AROPE rate as shown in Figure 4.1. As the AROPE indicator combines information on income, consumption/material deprivation and employment in the calendar year preceding the survey ([80]), effects can appear lagged by about 1 year. With the exception of 2013, the AROPE rate kept rising in the euro area between 2009 and 2014. From 2015 until 2018 the trend turned sharply, approximately returning to the levels before the crisis.

The crisis had fundamental impacts on the economies of the six Member States considered in this chapter (Figure 4.2). Already before the crisis, the AROPE rates in Spain and Italy were well above the euro area average (EAA). This gap increased considerably during the crisis to more than 4 p.p. in Spain and almost 6 p.p. in Italy. The remaining four countries started below the EAA and markedly improved their relative positions during the crisis. In 2018, the AROPE rates in France and Austria were about 4 p.p. below the EAA. Czechia and Slovakia made particularly fast progress. In Slovakia the AROPE rate was about 1 p.p. below the EAA in 2007, dropping to almost 6 p.p. below in 2018. This marks approximately the starting point in 2008 for Czechia, which reduced AROPE sharply to close to 10 p.p. below the EAA in 2018.

Figure 4.1: AROPE rate (dashed line, left-hand side axis) and real GDP per capita (solid line, right-hand side axis) in the 19 euro-area countries during the crisis, 2007–2018

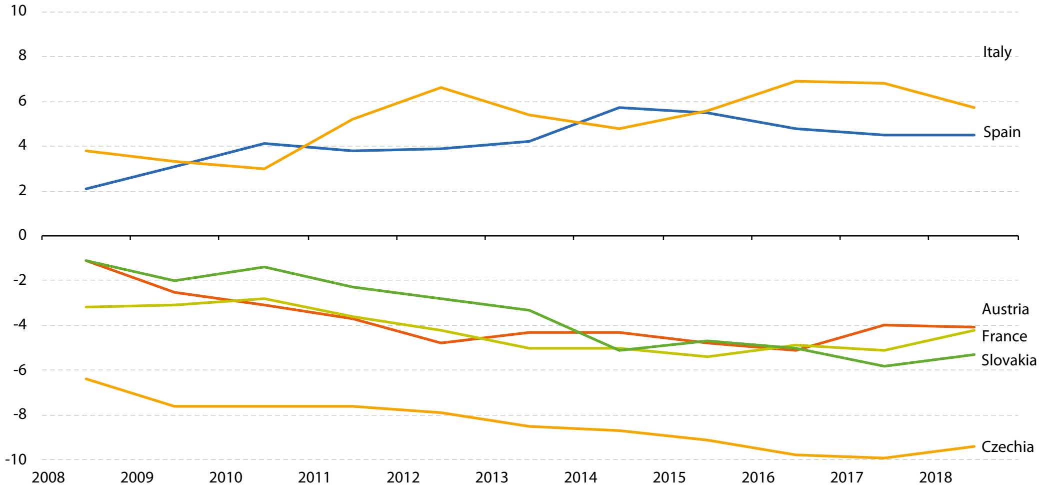


Reading note: Real GDP per capita across the 19 countries of the euro area was just below EUR 29 500 in 2007 and reached almost EUR 31 000 in 2018. The AROPE rate reached its peak in 2014 at about 23.5 %.

Sources: Eurostat SDG_08_10 and T2020_50.

([80]) The income reference period refers to the previous calendar year, which is also the basis for calculating low work intensity. Certain deprivation questions (e.g. arrears in the previous 12 months) refer to a period in the past that may cover several months preceding the interview.

Figure 4.2: AROPE difference for six EU Member States compared with the euro area during the Great Recession
(percentage points above/below the euro-area AROPE rate)



Reading note: In 2008, the AROPE rate for Italy was about 4 p.p. above that of the EAA. By 2018 this changed to about 6 p.p. above the EAA AROPE rate.
Source: Eurostat T2020_50.

4.6. Mapping structural disparities in six countries

Eurostat publishes the AROPE rate and its components for NUTS 2 regions (table TGS00107). However, regional data are available only for four out of the six countries considered here. There are no data on France throughout the period, and for Austria only the years 2014–2017 are included. Although the database also sets out confidence intervals, these are available only for Austria. The results would suggest a consistent increase in AROPE rates from north to south, with the highest rates in the south of Italy and the south of Spain. However, a broad regional classification such as NUTS 2 fails to capture heterogeneity within those regions (e.g. between rural and urban areas).

The most recent Eurostat regional yearbook (Eurostat, 2019) addresses spatial inequalities with regard to the degree of urbanisation. It reveals that, among the six countries considered here, Spain, Italy and Austria have particularly high AROPE rates in their cities. In Austria and Slovakia, the inequality between urban and rural areas appears substantial, although it goes in opposite directions. In Austria, cities stand out as having the highest AROPE rates, while in Slovakia the rural areas appear much more disadvantaged. There is, however, no combined disaggregation by region and degree of urbanisation yet ([81]).

The incompleteness of the data that are disseminated points to a serious shortcoming of the present capacity of EU-SILC to capture cohesion. Consequently, these results would not allow a consistent assessment of whether or not the crisis had actually changed anything at subnational level.

This chapter disaggregates the population of the six countries into 126 areas. Generally, these areas represent NUTS 2 regions, which have been split between urban areas and non-urban areas. The latter lumps together two categories of the Degurba classification, comprising rural areas and areas

([81]) As a convention, poverty lines are defined only at national level. While regional poverty lines, which could implicitly or explicitly account for regional price differences (e.g. housing costs), could possibly improve their validity, the magnitude of such non-sampling errors may in practice often be outweighed by errors due to very small sample size (see Verma et al., 2010).

with intermediate population density. For Italy, only the broader NUTS 1 regions could be used. Statistics Slovakia made NUTS 3 regions available for the years after 2015 but no further differentiation between urban and non-urban was possible.

Figure 4.3 provides a detailed view of the AROPE rate and 95 % confidence interval for each of the 126 regions. Calculations are based on AAA with bootstrapped standard errors over 2016–2018 ([82]) (Till et al., 2018). Results with a standard error exceeding 2.5 p.p. (i.e. a confidence interval of roughly 5 p.p. in each direction from the point estimate) are provided. Urban and non-urban areas are represented as triangles and dots. It can be seen that within regions the AROPE rates in urban areas often appear rather different from those in non-urban areas. However, the sample size is usually too small to observe statistically significant differences. Non-overlapping error bars for urban and non-urban areas are observed within three NUTS 2 regions (ES12, ES21, FR10), confirming that disparities by degree of urbanisation are significant.

For 70 out of the 126 areas considered, the AAA2016–2018 estimates have a standard error of less than 2.5 p.p. Without cumulation, only 47 areas would retain similar precision.

Figure 4.4 summarises the gain in precision by plotting standard errors of the cumulated estimates against the single-year estimate. It can be seen that standard errors of AAA are estimated to be approximately 25 % lower than standard errors of the single-year estimates, which is the equivalent of an increase of 78 % in effective sample size ([83]).

Obviously, the precision gain can be increased when more data points are cumulated together ([84]). Figure 4.5 presents results using data from 11 EU-SILC years, from 2008 to 2018, to reflect long-term structural disparities between Europe's regions. In this figure the AROPE rate is expressed as a difference in p.p. from the average of the euro area, thus taking away the effect of changing overall AROPE levels in times of crisis. The estimated AROPE rates are classified using symmetric intervals around the EAA, with each bracket comprising 5 p.p. Results with a standard error exceeding 2.5 p.p. are suppressed and highlighted by grey shading. This rule corresponds to a relatively broad 95 % confidence interval of roughly 5 p.p. This represents the width of each category in Figure 4.5. What can be clearly seen is the stark contrast between the AROPE rates in the south of Spain and Italy and in the more northern regions.

4.7. Quantifying regional cohesion

Once regional breakdowns of indicators are available, they also provide a basis for quantifying the overall disparity between regions within a country. For example, the dispersion of employment rates is sometimes expressed by the coefficient of variation. This indicator is defined as the ratio of the standard deviation of the regional means to the (weighted) mean across regions.

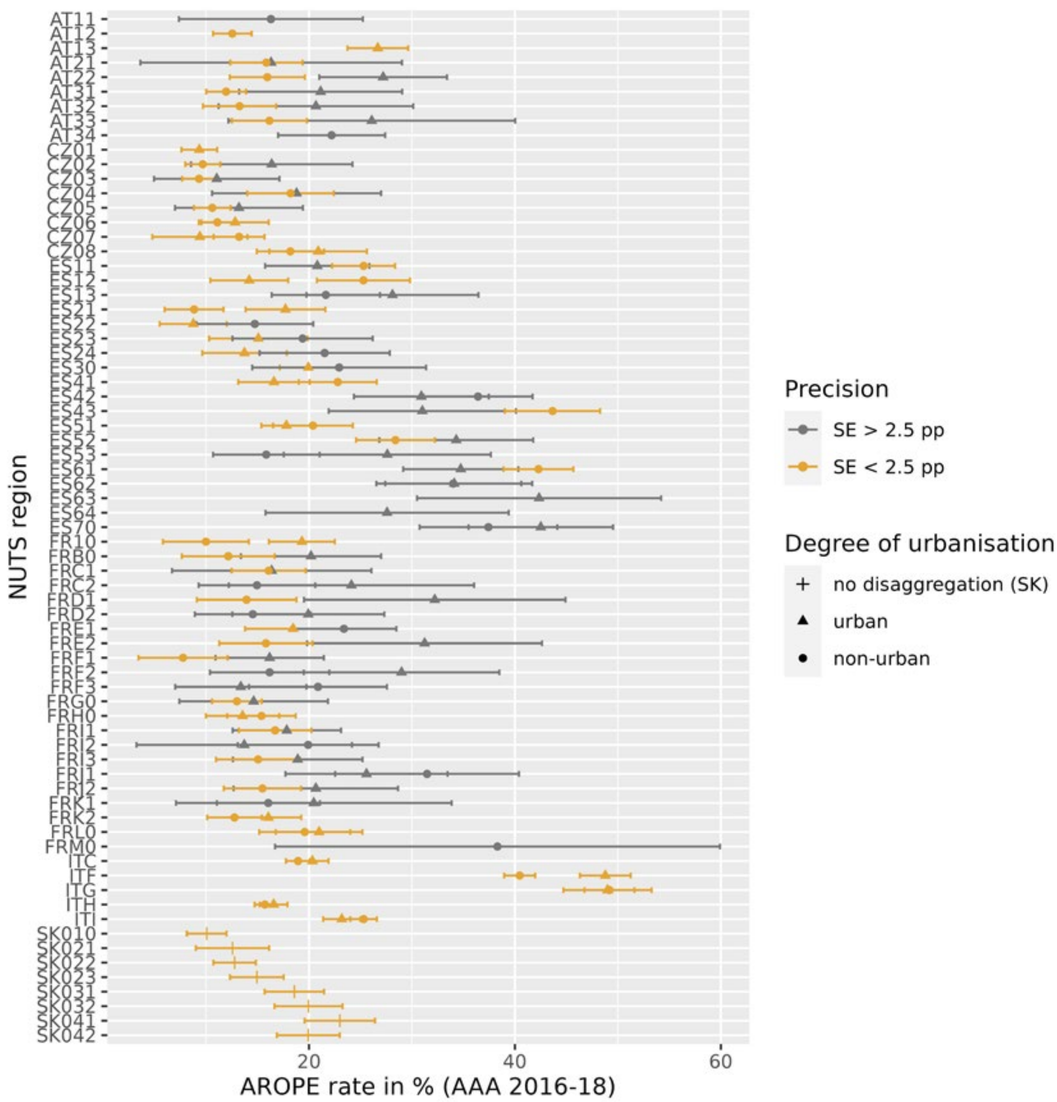
However, the number and size of regions vary between countries, which limits the comparability of such a measure between countries. Results may also be very much influenced by small outlier regions. The choice of regional level is therefore critical. If the measure is based on small units, such as the districts of a big city, this will inevitably reflect greater dispersion than, for example, a measure of disparity between NUTS 1 regions, which in some cases may comprise the entirety of a small country. One possible strategy to improve comparability of the coefficient of variation is to base it on breakdowns at the lowest level possible, because their sizes will be of similar magnitudes.

An alternative measure would express the gap between the regions that are most disadvantaged and those that are furthest ahead of the others. Verma et al. (2005a,b) proposed such a measure,

([82]) For Slovakia, results refer to 2015–2018 only.
([83]) It may seem surprising that standard errors of the cumulated estimates are in fact higher for six regions. In four of these regions sample sizes did increase slightly. In all these regions the point estimate for 2018 is lower than the 3-year average. Sampling errors depend both on the size but also on the value of the point estimate. Without changing sample size, the sampling error increases as the percentage increases towards 50 %. Hence a lower point estimate can also contribute to a lower sampling error.
([84]) Using a broad time span to reduce variability of estimates may, however, come at the cost of producing results that are biased towards the past. This trade-off is especially relevant when major transitions can be expected to have taken place.

Figure 4.3: **Standard errors for AROPE rates in urban and non-urban regions of six Member States (AAA, 2016–2018)**

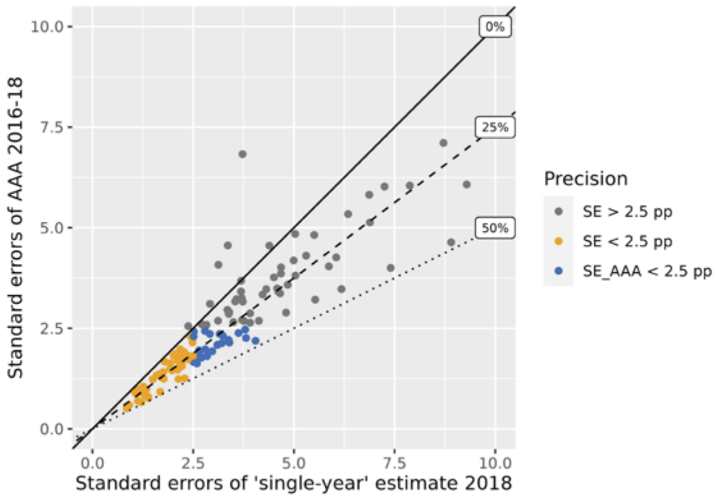
(%)



Note: AT13 (Vienna) is represented by a single triangle symbol because the region contains no non-urban area. AT12 (Lower Austria) is represented by only a single dot, as no urban area exists in that region. The symbols are surrounded by error bars, which represent the 95 % confidence interval. For the two regions, error bars are yellow, which indicates that the standard error (SE) is smaller than 2.5 p.p. The error bars do not overlap between these regions. The difference is to be assumed significant. By contrast, the dot for AT11 (Burgenland, non-urban) is surrounded by a very large (grey) error bar, significantly exceeding 2.5 p.p. This reflects the small sample size in this (small) region. The error bar for AT11 also overlaps with the error bars of both AT13 and AT12 and thus cannot be considered statistically different from either of those even on the basis of the cumulated estimates from 3 years.

Sources: Authors' computations, UDB 2018-2, additional regional classifications and identifiers provided by statistical offices of Spain, Austria and Slovakia.

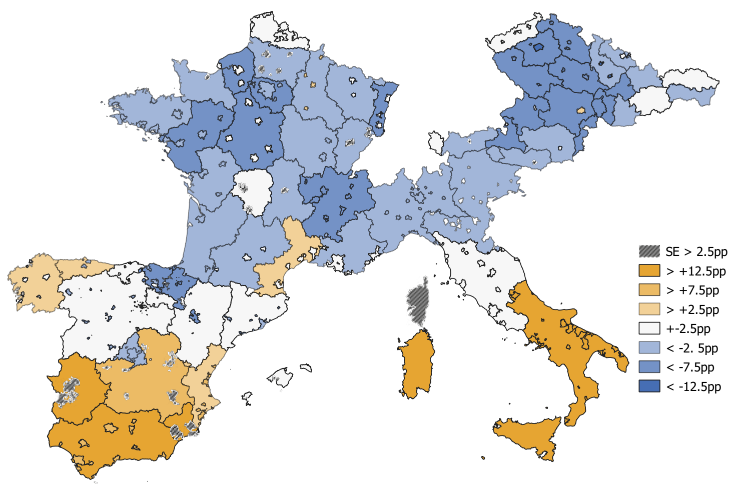
Figure 4.4: Precision gained when using AAA 2016–2018 to estimate AROPE in regions



Note: Each point represents standard errors (SE) for 1 of 122 areas in the six countries considered (4 outliers have been excluded for better visual representation). Grey points represent areas where no robust AROPE estimate is available. Blue points represent areas where the standard error is reduced below 2.5 p.p. when data are cumulated, while yellow points reflect those regions where the single-year estimate would already be sufficiently precise. Points below the 25 % diagonal refer to regions where the standard error of the AAA estimate is reduced by at least 25 % compared with the 2018 estimate.

Sources: Authors' computations, UDB 2018-2, additional regional classifications and identifiers provided by statistical offices of Spain, Austria and Slovakia.

Figure 4.5: AROPE differences from the euro area in regions of six EU Member States (2008–18) (p.p.)



Note: The map does not display three Spanish regions: standard errors (SE) for AROPE in ES63 (Ceuta) and ES64 (Melilla) are above 2.5 p.p. For urban areas in ES70 (Canary Islands, not displayed on map), the long-term AROPE rate was more than 12.5 p.p. and in non-urban areas 7.5 p.p. above the EAA.

Reading note: For all countries except Slovakia, the map displays urban and non-urban areas within regions. Areas where the AROPE rate was below the EAA are highlighted in blue; those above the EEA are highlighted in orange. For example, the areas in the south of Spain and Italy had AROPE rates that were consistently above the EEA. The grey-shaded areas (e.g. Corsica) indicate that standard errors are too high.

Sources: Authors' computations, UDB 2018-2, additional regional classifications and identifiers provided by statistical offices of Spain, Austria and Slovakia.

analogous to the S80/S20 indicator, which is widely used to assess income inequality at individual level. Applied to regional disparity, this parameter simply ranks regions and presents the ratio between the weighted average indicator for the top regions and that for the bottom regions. In this approach, differences in the size of regions are handled by weighting. This simple regional quintile ratio (RQR) is especially useful to quantify spatial inequality across countries when regional breakdowns can be measured with reasonable precision ([85]).

When we calculate the RQR for AROPE indicators (AAA2016–18) for 126 regions in the selected six countries, we find the lowest spatial inequality in France and the highest spatial inequality in Italy (Table 4.2). The RQR for France was estimated at 1.5. This can be interpreted such that the AROPE rate in France's poorest regions is only about 1.5 times as high as in France's richest regions. By contrast, Italy's poorest regions, in the south of the country, have an AROPE rate that is 2.4 times the magnitude of that in the richest regions, in the north of the country. Estimates for the other countries lie between those extremes. The proportionate weighting of regions ensures that in each country 'poorest' and 'richest' refer to an equal share of the population ([86]).

Table 4.2: Degree of disparity in six EU Member States (RQR based on AAA2016–18 AROPE rates)

Member State	RQR (AAA2016–18)
France	1.5
Slovakia	1.7
Czechia	1.8
Spain	2.0
Austria	2.2
Italy	2.4

Reading note: An RQR of 1.5 for France implies that the AROPE rate for its poorest areas is only about 1.5 times as high as in its richest areas, defined on the basis of NUTS 2 regions while distinguishing urban and non-urban areas on the basis of the Degurba classification.

Sources: Authors' computations, UDB 2018-2, additional regional classifications and identifiers provided by statistical offices of Spain, Austria and Slovakia.

([85]) Verma et al. (2005a,b) also proposed a measure that takes into account not only differences in size of regions but also the associated standard error.

([86]) The procedure includes an interpolation whereby the AROPE rates of the regions that include the 20th and 80th population percentiles are proportionately considered. The algorithm can be provided as a short R code by the author upon request.

4.8. Have regional patterns changed over the past decade?

For most regions, changes have been too small to be detected by the available sample power from EU-SILC. Results also have to be interpreted with some caution, considering the possibility that artefacts may occur, for example, when administrative boundaries of the areas may have changed over the 11-year period from 2008 to 2018. If anything, the structural picture shown in Figure 4.5 seems to have been only aggravated during the crisis. When comparing the available regional data from 2018 with 2008 (or 2015 in the case of Slovakia), we do, however, find 14 areas where the AROPE rate changed significantly ([87]).

Table 4.3 lists those areas where the AROPE rate was significantly higher in 2018 than it was in 2008. EU-SILC suggests a slight deterioration in urban Cantabria (ES13) and non-urban areas in southern Spain (ES43, Extremadura, and ES61, Andalusia) and the urban areas of southern Italy (ITF). All estimates are subject to relatively large sampling errors, exceeding 3 p.p. Considering the lower limit of the 95 % confidence interval, we must conclude that the largest increase occurred in the urban part of the Centre region (ITI) in Italy ([88]).

On the other hand, Table 4.4 shows that all countries except Italy have at least one area in which AROPE decreased significantly. The largest reduction in the AROPE rate over the last decade was seen in the urban part of the Lorraine region (FRF3) in France. Considering the sampling error, the reduction can be assumed to have exceeded at least 5 p.p. (lower limit of the 95 % confidence interval). By contrast, for the urban part of the Brittany region in France a reduction of at least 1 p.p. is assumed, considering sampling errors. A somewhat stronger reduction must be assumed for Central Moravia (CZ07), Lower Austria (AT12) and the Bratislava region (SK010).

([87]) Excluding one region (FRD1), which has only about 135 observations.

([88]) The largest increase in the AROPE rate was observed for urban areas in FRD1 (Lower Normandy). According to EU-SILC data, the AROPE rate would have increased by at least 11 p.p. (lower limit of the 95 % confidence interval). Considering the possibility of artefacts such as changes in administrative boundaries of the areas, together with the extremely large confidence interval and the small number of observations, this result is not presented in the table.

Table 4.3: Regions with significant increase in AROPE rates between 2008 and 2018 in Spain and Italy

Country	Region	NUTS	Degurba	Difference (p.p.)	Standard error	95 % confidence interval of p.p. difference (lower limit)
Spain	Cantabria	ES13	Urban	13.7	7.0	0.1
	Extremadura	ES43	Non-urban	8.5	4.2	0.3
	Andalusia	ES61	Non-urban	7.2	3.1	1.1
Italy	South	ITF	Urban	7.5	3.2	1.3
	Centre	ITI	Urban	6.9	2.1	2.8

Reading note: The AROPE rate that was measured for 2018 in the urban part of the Italian Centre region is 6.95 p.p. above its value in 2008. The sampling error for this estimate was calculated to be 2.1 p.p., which gives a lower limit of 2.8 % for the 95 % confidence interval. It is unlikely that the increase was smaller than that.

Sources: Authors' computations, UDB 2018-2, additional regional classifications and identifiers provided by the Spanish statistical offices.

Table 4.4: Regions with significant reduction in AROPE rates between 2008 and 2018 in five countries

Country	Region	NUTS	Degurba	Difference (p.p.)	Standard error	95 % confidence interval of p.p. difference (lower limit)
France	Lorraine	FRF3	Urban	17.1	6.1	5.2
Slovakia	Bratislava	SK010	n.a.	8.4	2.7	3.0
Austria	Lower Austria	AT12	Non-urban	5.3	1.8	1.6
Czechia	Central Moravia	CZ07	Non-urban	5.9	2.5	1.1
France	Brittany	FRH0	Urban	10.5	4.8	1.0
Slovakia	Trenčiansky kraj	SK022	n.a.	5.1	2.3	0.6
Czechia	South-East	CZ06	Non-urban	3.7	1.7	0.3
Czechia	Central Bohemia	CZ02	Non-urban	3.7	1.8	0.2
Spain	Balearic Islands	ES53	Non-urban	12.5	6.3	0.1

Note: Regions ranked according to the last column (significant difference from no change); n.a.: not available.

Reading note: The AROPE rate that was measured for 2018 in the non-urban part of the Balearic Islands is 12.5 p.p. below its value in 2008. The sampling error for this estimate was calculated to be 6.3 p.p., which gives a lower limit of 0.1 p.p. for the 95 % confidence interval. It is unlikely that the reduction was smaller than that.

Sources: Authors' computations, UDB 2018-2, additional regional classifications and identifiers provided by statistical offices of Spain, Austria and Slovakia.

4.9. Conclusion

The results presented in this chapter demonstrate the future potential of EU-SILC for regional analysis and indicators relevant to it. To make further progress, priorities are suggested as follows:

1. improve access to existing information;
2. document and especially adapt survey designs for regional analysis;
3. publish results that use enhanced methods for indicators and standard errors.

First of all, as already noted by Verma et al. (2010), the analysis of regional disparities with EU-SILC is hampered by the lack of information in the UDB. The fact that the IESS regulation includes reformulated precision requirements for the AROPE and the persistent AROP indicators at NUTS 2 level (see Chapter 20 of this volume) is an important step forward, which offers encouraging prospects. Yet more regional information available at country level should be included in the UDB. This is particularly important given the potential relevance of regional disaggregation for regional funding decisions. To improve the analysis of policy effectiveness, the degree of urbanisation, as well as the regional identifiers (at least at NUTS 2 level - DB040), should be included in the UDB for all countries. In reality, disclosure concerns are very unlikely to apply, since many socioeconomic characteristics could already be disaggregated to much greater detail. As regional aggregates vary greatly in size and number across countries, it is highly advisable to provide data for all countries at the lowest possible level. Using NUTS 3-level regional identifiers would minimise the difference in the average size of regions and would allow an assessment of regional disparities that would be more comparable across countries.

Second, the legitimate concerns regarding the robustness of regional estimates need to be addressed actively by carefully assessing the sampling precision, as required in the framework regulation. Today, data analysts who wish to calculate confidence intervals for their estimates need to reconstruct crucially relevant sample design information in most cumbersome ways (Goedemé, 2010). It is essential that all sample design variables (e.g. DB050 and DB060) be disclosed to users, the quality of this information must be regularly checked and codes should be harmonised across all waves and rotations. Alternatively, it would be a great service to users if calibrated replicate weights were provided (Till et al., 2018). To further improve the robustness of estimates, Member States should perhaps consider always stratifying their samples for all urban and non-urban NUTS 2 (or NUTS 3) regions. As a rule of thumb, standard errors below 2.5 p.p. for an assumed AROPE rate of approximately 20 % of the population would require an effective sample size of at least 250 households for each of these strata. This basic sample size would have to be increased accordingly in the case of multistage sampling, high non-response rates or especially high AROPE rates. For almost half of the regions considered in this chapter, the sample comprised fewer than 300 households, which indicates that ultimately a substantial increase in or reallocation of the sample would be necessary.

Finally, this chapter has demonstrated that, even if the effective sample size of EU-SILC cannot guarantee the same precision as, for example, the ACS, a lot more could be done to provide empirical data for decision-making. As a minimum, all Member States should provide either NUTS 3- or NUTS 2-level estimates on poverty indicators, disaggregated by urban and non-urban areas where sample sizes allow this, to be disseminated through the Eurostat database. It is essential that these estimates include an indication of their sampling error. To enhance precision, it is recommended to apply AAA and calculate standard errors for these estimates. On that basis, it will also be possible to monitor regional convergence by indicators of disparity such as the RQR presented in this chapter.

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5 Foreign-born households in the income distribution and their contribution to social indicators in European countries

Alessio Fusco, Rhea Ravenna Sohst and Philippe Van Kerm (89)

5.1. Introduction

The general public notoriously holds incorrect views about the foreign-born population in their countries – most notably, the share of immigrants is often vastly overestimated and the perception of their impact on various social and economic areas exaggerated (Alesina et al., 2018). The academic debate about the impact of immigration on the distribution of income in host countries is contentious too (see, for example, Card, 2001, 2009; Blau and Kahn, 2015). Multiple studies have indeed found a concentration of immigrants at both tails of the income, occupation and skills distributions in the host country; for example in Luxembourg (Amétépé and Hartmann-Hirsch, 2011; Fusco et al., 2014), Switzerland (Müller and Ramirez, 2009) and the United Kingdom (Dustmann et al., 2013). However, the implications of this polarisation for overall levels of income and social inequality in European countries remain unclear.

Against this backdrop, we exploit EU-SILC data to provide new evidence on the relative position of foreign-born households within the income distributions of 28 European countries, and their contribution to commonly agreed EU social indicators of poverty, inequality, material deprivation and social exclusion. We define foreign-born households as those where all members aged 16+ are born outside their country of residence.

The chapter has three parts. We first review the coverage of immigrant populations in EU-SILC. We then compare average income and deprivation measures of foreign-born and native-born households. Finally, we use influence function (IF) regression methods to derive the implications of differences in the relative income position (and exposure to deprivation) of foreign-born households for seven key social indicators and assess if foreign-born households' income and deprivation levels are pushing national inequality and poverty indicators upwards.

We find that individuals living in foreign-born households have lower incomes and higher levels of poverty and deprivation in all countries examined. No clear improvement in the relative position of foreign-born households is observed between 2007 and 2018. Although there is much heterogeneity in the income of foreign-born households, their generally disadvantaged situation implies that, on the whole, they tend to push inequality, poverty and deprivation indicators upwards. This effect persists in many countries, albeit mitigated in magnitude when we account for the different demographic, education and employment characteristics of immigrants compared with natives.

(89) Alessio Fusco is with LISER, Ravenna Sohst with the University of Luxembourg, and Philippe Van Kerm with the University of Luxembourg and LISER. The authors are grateful to participants in the Semilux seminar, David Marguerit, Ioana Salagean and the editors for comments and suggestions. This work was supported by Net-SILC3, funded by Eurostat and coordinated by LISER. Ravenna Sohst is supported by the Luxembourg National Research Fund (MINLAB DTU 10949242). The European Commission bears no responsibility for the analyses and conclusions, which are solely those of the authors. Email address for correspondence: philippe.vankerm@liser.lu

5.2. Immigrants in EU-SILC samples

5.2.1. Coverage

Our analysis relies on 2007 and 2018 EU-SILC cross-sectional data. A critical question is the reliability of EU-SILC for a study about immigrant populations. At least three problems can arise: (1) undercoverage of immigrant populations due to EU-SILC design, (2) undercoverage due to differential non-participation and (3) small sample sizes. By design, recent migrants may not yet be included in the sampling frame, leading to undercoverage of this group. In addition, the target of EU-SILC for private households excludes persons living in collective households or institutions from the sampling frame. This can lead to undercounting of the most vulnerable of immigrant groups, such as immigrants seeking humanitarian protection and living in reception centres and communal living arrangements; immigrants without legal residence; immigrants who change accommodation very frequently; and immigrants living in unregistered camps. By contrast, more established immigrant groups – for example immigrants from other EU countries, those who arrive through regular immigration channels and those who have lived in the country for a longer time – are more likely to be accurately represented in EU-SILC. In addition to the potential bias that could arise from the EU-SILC sampling frame, differences in response rates among immigrants and natives might aggravate undercounting of immigrants. One reason for low response rates is language or cultural barriers. Another reason is the particular reluctance of immigrants to participate in surveys, which can be a consequence of uncertainty regarding their legal status, previous experiences of discrimination or a lack of trust in public authorities (Font and Méndez, 2013). Finally, in the absence of targeted oversampling of foreign-born households, the number of foreign-born respondents in medium-sized samples such as EU-SILC is likely to be relatively small, in particular in countries with already small immigrant populations.

Bearing these reservations in mind, two observations are, however, reassuring. First, in 2017 the OECD assessed the absolute size of the migrant samples in several data sources (OECD, 2017). Comparing EU-SILC, the ESS, the OECD Survey of Adult Skills and the Gallup World Poll, they found that EU-SILC had by far the largest absolute number of migrants per country in its sample (on average 1 200 per country). Second, Figure 5.1 shows that, on average, national EU-SILC samples mirror official statistics to a considerable degree. The figure compares migrant proportions in 2018 EU-SILC samples with proportions published in official counts provided by Eurostat, separately for EU-born and non-EU-born immigrants [90]. The difference between the population share provided in the national EU-SILC samples and the official reference statistics is only –1.4 p.p. on average. Although we cannot rule out some bias due to differential coverage of the less vulnerable among the foreign-born households, the overall coverage of foreign-born populations in EU-SILC appears satisfactory. The rates, however, differ widely for three countries. Two of them, Cyprus (–5.9 p.p. underestimation of the share of EU-born migrants) and Malta (–12.2 p.p. underestimation of the share of all foreign-born) have been excluded from our analysis. Germany similarly displays a large gap between official Eurostat figures and its EU-SILC sample (–6.9 p.p. underestimation). However, Germany is a special case, since it is the only country that does not provide a breakdown of its foreign-born population by age groups in Eurostat. Figure 5.1 therefore compares the 16+ foreign-born population in EU-SILC with the total foreign-born population in Eurostat. This discrepancy suggests that the estimated gap for Germany lacks accuracy, especially given the large

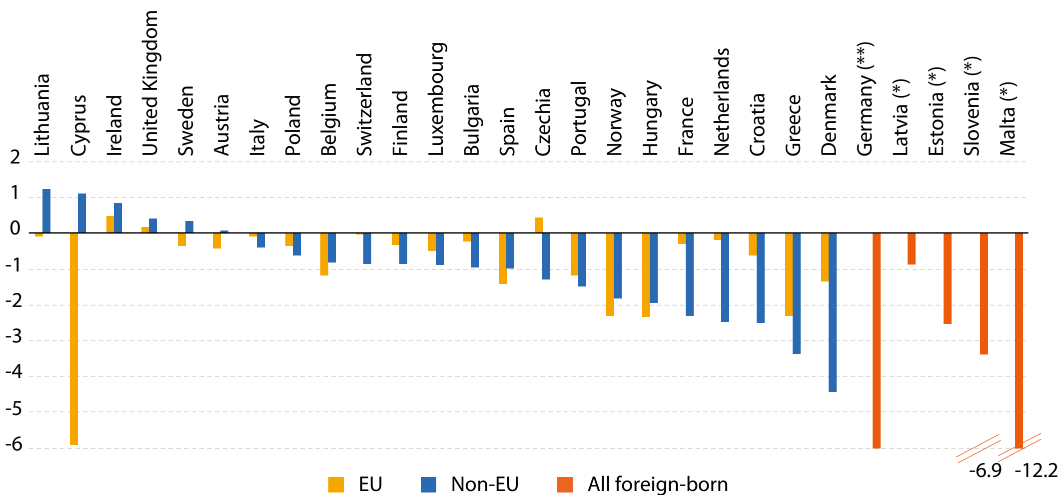
[90] The relevant Eurostat table is [migr_pop3ctb]. The table shows the population by country, age group, sex and country of birth. The calculations of the difference between shares of the foreign-born population in EU-SILC and Eurostat are based on countries that are available in both data sources in the given years. For 2007, a majority of data points is missing because the country of birth of the foreign-born population is not reported by Eurostat (except for Ireland, Spain, France and Lithuania). Note that information on the country of birth in EU-SILC is only available for respondents aged 16+. However, because of the predefined age groups in the Eurostat data, the comparison group comprises the foreign-born populations aged 15+, and not 16+ as in the EU-SILC data. There is a slight overestimation of the difference between the two data sources, which is due to the inclusion of 15-year-olds in the Eurostat data.

share of foreign-born among children in this country [91]. We therefore keep Germany in our sample.

It remains true that the size of the foreign-born samples is small in a few cases. Even though the methodology that we adopt here does not necessarily require large samples, we set a threshold of at least 50 observations in the unweighted sample for inclusion in our study to be in line with the reliability levels defined by the EU-SILC publishing guidelines (European Commission, 2020). Bulgaria and Romania each had fewer than 50 individuals reportedly living in entirely foreign-born households in both 2007 and 2018 and are therefore excluded from our analysis [92]. (See Section 5.2.2 for the definition of 'foreign-born households'.)

Our analysis therefore covers a base set of 28 countries that provided EU-SILC data in 2007 and/or 2018: all EU-27 Member States minus Bulgaria, Cyprus, Malta and Romania, plus Iceland, Norway, Serbia, Switzerland and the United Kingdom. Iceland and Slovakia are included in the 2007 EU-SILC but not in 2018, and are therefore not shown in figures and tables referring to 2018 only. Thus, 26 countries are covered in analyses based on 2018, unless otherwise specified.

Figure 5.1: Foreign-born proportions in EU-SILC compared with national counts, population aged 16+ (EU-SILC) and 15+ (Eurostat), 2018
(p.p.)



Note: The figure shows the population share of foreign-born persons aged 16+ in EU-SILC or 15+ in the national reference statistics taken from Eurostat. Countries are shown in descending order of the difference between EU-SILC estimates and national counts for non-EU-born immigrants. National counts are not available for Serbia. Iceland and Slovakia are not covered in the 2018 EU-SILC.

(*) In EU-SILC, Estonia, Latvia, Malta and Slovenia do not reveal information on country of birth. Their values therefore refer to the sum of EU-born and non-EU-born immigrants.

(**) Germany also does not distinguish EU-born from non-EU-born immigrants, but it also does not break down its foreign-born population by age groups in the statistics provided to Eurostat. The German value therefore compares the foreign-born population aged 16+ in EU-SILC with the total foreign-born population in Eurostat data.

Reading note: Compared with national reference values, the Belgian EU-SILC sample underestimates the population share of EU-born immigrants by 1.2 p.p. It underestimates the share of non-EU-born immigrants by 0.8 p.p.

Sources: Authors' computations, UDB September 2019 and Eurostat table [migr_pop3ctb], from which we calculate population shares.

(91) In Germany, the share of persons with a migrant background is over 38 % for children under the age of 5 but only 16 % for persons between 55 and 65 years (Bundeszentrale für politische Bildung, 2018).

(92) When split by EU/non-EU origin, samples were fewer than 50 observations for individuals living in entirely EU-born households in Croatia, Lithuania and Poland in 2018, and in Lithuania, Hungary and Portugal in 2007. For the non-EU-born samples, they were below the threshold in Hungary in 2018, and in Slovakia in 2007. We decided, however, to apply the exclusion rule to the total number of immigrants only.

5.2.2. Defining foreign-born households in EU-SILC

There is no single definition of an immigrant. Two concepts are typically used, both of which are available in EU-SILC: country of birth (variable PB210) and citizenship (PB220A). We use here the country of birth definition because, unlike citizenship, it remains fixed throughout a person's life (93). Furthermore, the legal frameworks regulating access to citizenship vary widely across countries, which hampers comparability.

Our analysis is performed at individual level but all conditioning variables are constructed at household level. There are two reasons for this. First, EU-SILC collects information on the country of birth only for persons aged at least 16 years. To keep children in our analysis, we constructed an 'immigrant status' indicator at household level based on the country/ies of birth of all adult household members. Second, income, a key variable of our analysis, is constructed at household level. Like for the immigrant indicator, the same value is attributed to each member of a household. We therefore construct most conditioning variables as continuous or quasi-continuous within-household shares (Brzezinski, 2018): the share of women in the household, share of married or separated members, shares of members falling into two age groups (working age, 26–64, and seniors, above 64), share of tertiary-educated members and activity status shares. Finally, we also include the household composition (number of adults + number of minors) among our conditioning variables.

To construct a household-level indicator of immigration status, we combine the individual country-of-birth information of all household members. In the UDB, country-of-birth information is normally aggregated into three groups: (1) local, that is, same country as country of residence, (2) EU, that is, any Member State except country of residence, and (3) non-EU. On this basis, we distinguish five non-overlapping groups based on the country of birth of each household member aged 16 and older:

1. native – all household members aged 16+ native born;
2. mixed foreign/native – mix of foreign- and native-born household members;
3. EU – all members aged 16+ born abroad in an EU country;
4. mixed EU/non-EU: all members aged 16+ born abroad, in both EU and non-EU countries;
5. non-EU – all members aged 16+ born in non-EU countries.

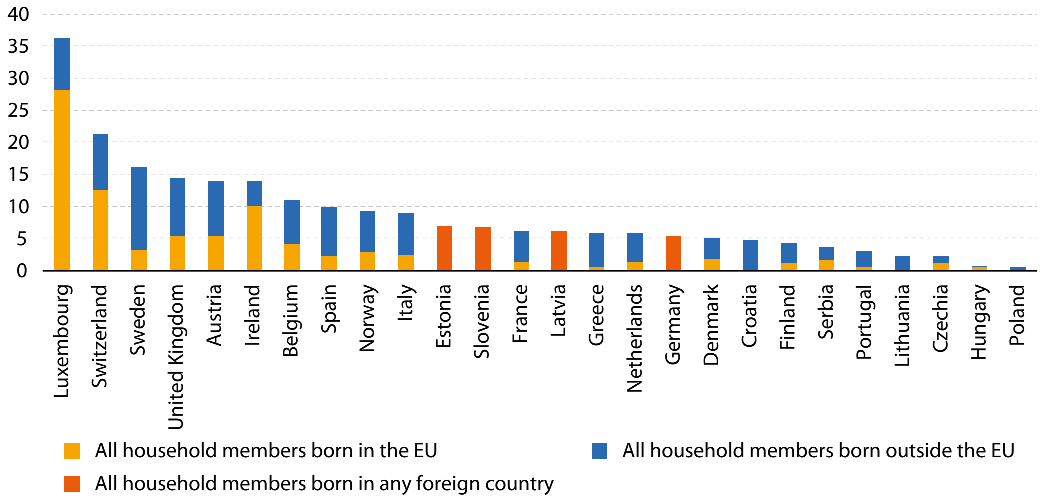
Sample size concerns are critical for mixed households, and in Section 5.4 we therefore focus only on how groups 3 and 5 compare with group 1.

Unfortunately, not all countries distinguish the EU born from the non-EU born. For Germany, Estonia, Latvia and Slovenia we therefore construct a simplified classification in which we only distinguish all-native from all-foreign-born households.

Figure 5.2 shows the share of individuals living in entirely EU-born (group 3) or entirely non-EU-born (group 5) households based on the 2018 EU-SILC sample.

(93) However, borders can be redrawn and countries can come into existence or disappear over the course of history. The EU-SILC identifies the country of birth using national boundaries in place at the time of the survey, not at the time of birth, in most cases (except where national minorities live abroad; see the EU-SILC 2017 codebook on the variable PB210 "Country of birth" for more details) (Eurostat, 2017). In regions where boundaries have shifted a lot, the EU-SILC strategy might lead to an incorrect identification of immigrants. For example, a person born in the former Yugoslavia might be categorised as an immigrant if they were born on territory that now belongs to Serbia but live on territory now belonging to Croatia. At the time of Yugoslavia's existence, their move happened within national bounxdaries, but, according to the EU-SILC definition, that person would be considered foreign-born.

Figure 5.2: Share of individuals living in foreign-born households by country, 2018
(% of weighted sample)



Note: Germany, Estonia, Latvia and Slovenia do not reveal information on the country of birth beyond local/non-local. In these countries, the shares in the figure therefore refer to households in which all household members aged 16+ were born in any foreign country, EU or non-EU. Iceland and Slovakia are not covered in the 2018 EU-SILC.

Reading note: 36 % of individuals in Luxembourg live in entirely foreign-born households, 28 % in EU-born households (group 3) and 8 % in households composed of non-EU-born members only (group 5). In Germany, 6 % of individuals live in households in which all members were born outside Germany.

Source: Authors' computations, UDB September 2019.

5.3. Foreign- and native-born living standards compared

Foreign-born households, both EU and non-EU, are on average worse off than entirely native-born households. Table 5.1 shows estimates of the ratio between foreign-born and native-born average equivalised disposable household incomes and AROPE rates (see Chapter 1 for a definition of this indicator).

It is clear from Table 5.1 that the average foreign-born household fares worse than the average native-born household in almost all countries. For example, 11 out of 22 countries (not considering Germany, Estonia, Latvia and Slovenia) in 2018 revealed significantly lower average incomes among non-EU-born households than native households. In many countries, those households earned on average less than two thirds of the amount that native households earn. Although both EU-born and non-EU-born immigrants appear to be disadvantaged in terms of income, the gap is significantly larger for immigrants from outside the EU in over one third of countries. Immigrants are more often AROPE, too. In 8 out of 22 countries in 2018 (Austria, Belgium, Denmark, France, Luxembourg, the Netherlands, Norway and Sweden), the share of non-EU-born households that were AROPE was over 3 times as high as the share of natives that were AROPE. Even for foreign-born households from other EU Member States, the share was more than double the share of natives in a range of countries, including for example Denmark, Spain, the Netherlands and Austria.

Table 5.1: Ratio of average income and AROPE rate between foreign-born and native households, 2007 and 2018

Country	Ratio of average income				Ratio of AROPE rate			
	EU-born to natives		Non-EU-born to natives		EU-born to natives		Non-EU-born to natives	
	2007	2018	2007	2018	2007	2018	2007	2018
Belgium	(1.00)	(0.96)	0.63	0.58	2.23	2.28	4.09	4.37
Czechia	(0.90)	(1.10)	(0.84)	(0.99)	2.11	(1.10)	2.54	2.03
Denmark	0.69	(1.03)	0.63	0.67	3.93	2.24	3.65	3.17
Ireland	0.80	0.85	0.69	(0.90)	1.70	(1.27)	2.35	1.93
Greece	(0.85)	0.72	0.66	0.62	(1.48)	2.34	2.15	2.15
Spain	(0.93)	0.68	0.69	0.57	1.84	2.41	2.00	2.82
France	0.83	0.83	0.72	0.68	1.56	1.88	2.61	3.49
Croatia	—	(0.81)	—	0.78	—	(1.52)	—	1.86
Italy	(0.94)	0.67	0.71	0.61	1.63	1.57	1.70	1.94
Lithuania	0.65	(0.84)	(0.92)	0.81	(1.89)	(1.23)	1.34	1.72
Luxembourg	(0.92)	0.86	0.64	0.66	2.10	1.78	5.46	3.51
Hungary	(1.22)	(1.25)	(1.05)	(1.09)	(1.09)	(0.76)	(1.03)	(2.30)
Netherlands	0.81	0.89	0.74	0.66	(2.03)	2.28	4.22	3.91
Austria	(1.00)	0.77	0.67	0.60	2.07	2.91	2.46	3.65
Poland	(0.94)	(0.86)	(1.09)	(0.99)	(1.22)	(1.34)	(0.99)	(1.21)
Portugal	(1.32)	(1.05)	(1.14)	(0.92)	0.36	(0.95	(0.89)	1.39
Slovakia	(0.91)	—	(0.8)	—	(1.16)	—	(0.87)	—
Finland	0.84	0.87	0.58	0.68	2.74	(1.1)	3.97	2.76
Sweden	0.86	0.79	0.67	0.60	2.44	1.76	4.05	4.33
Iceland	0.73	—	(0.83)	—	(1.25)	—	(1.55)	—
Norway	(1.02)	0.77	0.68	0.64	1.94	(1.46)	3.50	3.49
Switzerland	0.93	(0.99)	0.65	0.73	1.39	1.32	2.44	2.68
United Kingdom	(0.86)	(1.03)	0.83	(0.97)	2.35	(0.88)	2.22	1.49
Serbia	—	1.13	—	(1.13)	—	(0.78)	—	(1.09)

Country	Ratio of average income		Ratio of AROPE rate	
	All foreign-born to natives		All foreign-born to natives	
	2007	2018	2007	2018
Germany	0.82	0.88	1.66	1.44
Estonia	0.66	0.70	1.70	2.21
Latvia	0.72	0.76	1.49	1.95
Slovenia	0.77	0.76	1.88	2.46

Note: Statistically insignificant ratios at 0.05 level are reported in brackets. The ratios for Estonia, Latvia, Slovenia and Germany refer to all foreign-born households, EU- or non-EU-born. Cells marked with a '—' indicate that no data were available for that country and year. Iceland and Slovakia are not covered in the 2018 EU-SILC.

Reading note: In 2007, foreign-born households from outside the EU had an average income of 0.63 times that of native households in Belgium. In the same year, the share of households at risk of poverty or social exclusion (AROPE) was more than 4 times as large among non-EU-born households as among natives.

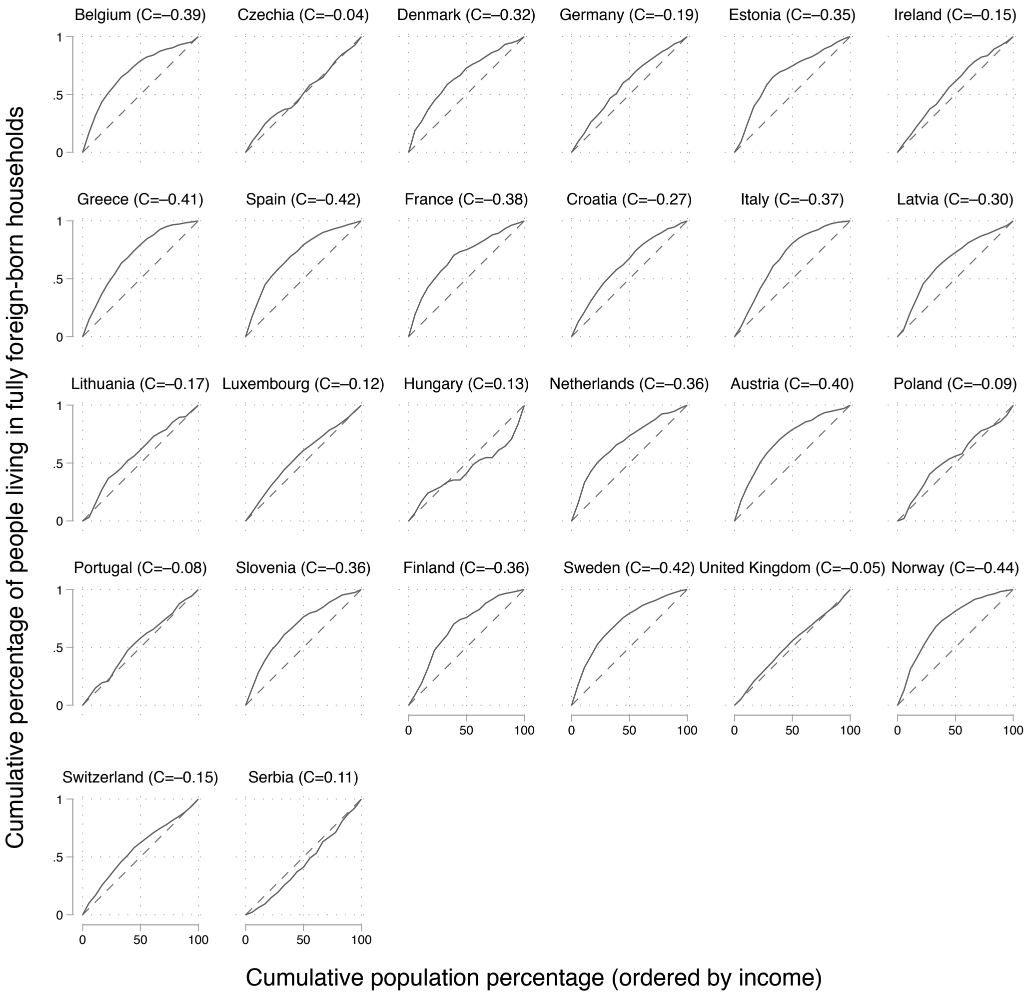
Source: Authors' computations, UDB September 2019.

Observing lower average living standards among foreign-born populations hardly comes as a surprise. Given their diversity, however, averages may hide more than they reveal. Figure 5.3 shows the concentration of the foreign-born population ranked along the income distribution (in 2018 only, for brevity). The figure plots the cumulative percentage of people living in fully foreign-born households (along the y-axis) against the cumulative percentage of the total population, ranked by disposable income from the lowest to the highest (x-axis). For example, the curves show at $x = 50$ the percentage of people living in foreign-born households that have an income at or below the national median. Foreign-born households are therefore over-represented in the bottom half of the income distribution if this percentage is larger than 50. The dashed 45° line marks the 'line of equality', that is, a reference situation in which the foreign-born would be equally distributed along income positions. The higher the concentration curves lies above the 45° line, the more concentrated foreign-born households are among the poorest. The concentration coefficient, also reported in Figure 5.3, is a numerical summary of the concentration curve. The concentration coefficient is equal to 1 minus twice the area between the diagonal and the concentration curve. It varies between –1 (all foreign-born concentrated among the poorest) and +1 (all foreign-born concentrated among the richest). A concentration coefficient of 0 describes a situation in which the foreign-born and native-born are equally distributed along the income distribution.

Most concentration curves are bent above the 45° line. This reflects immigrants' overall lower incomes and their concentration at the lower tails of the income distribution, since their population share is larger than their income share at the same point. Yet there is nuance to the picture. The foreign-born are most concentrated among the poorest in Norway (concentration coefficient of –0.44) and least concentrated in Czechia (–0.04) and the United Kingdom (–0.05). One exception to the broadly negative concentrations is Serbia, where the concentration line is below the 45° line and the concentration coefficient is positive at 0.11, revealing a (small) concentration of the foreign-born households among higher income relative to natives. Lastly, Hungary's curve crosses the 45° line, indicating that the foreign-born are overrepresented both among the poor and among the rich ([94]).

([94]) As noted earlier, the EU-SILC definition of country of birth can be challenging in countries where borders have shifted or national minorities live abroad. Both Serbia and Hungary might be affected by these particular difficulties.

Figure 5.3: The concentration of immigrants along the income distribution by country, 2018
(concentration curves and coefficients (C))



Note: Iceland and Slovakia are not covered in the 2018 EU-SILC.

Reading note: With a concentration coefficient (C) of –0.39 and the concentration curve bending high above the 45° line, foreign-born households in Belgium are strongly concentrated among the poorest. In contrast, foreign-born households in Switzerland are less concentrated among the poorest parts of the population than in Belgium. Its concentration coefficient is –0.15 and its concentration curve aligns with the 45° line at the 85th percentile, indicating that the income of foreign- and native-born households are similarly distributed at the top.

Source: Authors' computations, UDB September 2019.

5.4. Do foreign-born households influence social indicators?

Having established the reasonable coverage of EU-SILC and outlined the overall income and AROPE disadvantage of immigrants, we can now move to the main part of our analysis and examine whether or not foreign-born households can be said to influence (negatively) key social indicators. Like Choe and Van Kerm (2018) or Lin and Weiss (2019), we do so using IF regression methods (Firpo et al., 2009). In a nutshell, this approach empirically examines how much and in what direction marginally substituting a native household with a foreign-born household would affect estimates of a country's social indicators. This impact can be measured unconditionally – ignoring the fact that native and foreign-born households have different demographic characteristics, as done in the previous section – or conditionally on demographic covariates, in which case one captures the effect of substituting natives with foreign-born households having the same observable characteristics, such as age, education and employment. (See Chapter 17 of this volume for another application of this methodology; or Davies et al., 2017.)

We are looking at seven key social indicators: mean income, median income, the Gini coefficient, the AROP rate, the QJ rate, the SMD rate and the AROPE rate. The definitions of these indicators are provided in Chapter 1 of this volume.

To convey an intuitive idea of what IF regressions capture, think of three hypothetical situations ([95]). First, if immigrants are relatively more concentrated in the bottom of the national income distribution than natives, they can be thought to increase poverty and inequality and to decrease mean and median incomes. Second, in another hypothetical situation, if immigrants are relatively more concentrated among the upper income brackets, these effects will be reversed for the mean and median incomes and poverty (marginally increasing the share of immigrants would mechanically reduce poverty, since we would increase the share of the richer population) but would also increase inequality. Third, in a scenario where the income distributions of natives and immigrants were undistinguishable, immigrants would naturally not make any distinctive contribution to social indicators: increasing the share of immigrants relative to natives would not have any impact on distributional statistics, since both groups would have the same income. Estimating the impact of a notional (marginal) substitution of natives with foreign-born residents on distributional statistics therefore informs us about the position of immigrants' income relative to natives'. Estimates of these impacts are what IF regressions provide.

Relative to other methods – such as relative distribution methods (Handcock and Morris, 1998) – the first key advantage of IF regression is that it does not require direct estimation of income distributions for each group separately, so it does not hinge on having access to a large sample of foreign-born residents. This is particularly useful for analyses of medium-sized nationally representative survey data such as EU-SILC. The second advantage is that it is easy to control for differences in observable characteristics between natives and immigrants. As shown by Choe and Van Kerm (2018), adding covariates in IF regression models reveals how much of the difference in income positions is due to differences in observable characteristics between immigrants and natives (e.g. education, age and household demographic characteristics) and how much, if anything, is due to differences in income (or other deprivation indicators) unexplained by observable characteristics. We present both these unconditional and conditional results. Together they can provide information on the overall 'raw' contribution of immigrants and on the role of household characteristics such as household size and within-household share of activity status (see Section 5.2.2 for the list of variables used).

So how do foreign-born residents contribute to poverty, inequality and exclusion? How much is their contribution explained by differences in educational levels, employment and other demographic characteristics? Because of the large number of estimates that we produced, we pres-

([95]) We focus in this section on an intuitive approach to understanding IF regressions. For a rigorous description, see Firpo et al. (2009) or Choe and Van Kerm (2018).

ent only a subset of results, which we consider the most relevant ([96]). These are, first, the 2018 unconditional results (Table 5.2) and, second, the 2018 fully conditional results (Table 5.3) ([97]). The interpretation of the effects is parallel to how linear regression coefficients without and with controls would be interpreted. Positive estimates are marked with a '+', negative estimates with a '–'. Statistically insignificant results are put in brackets. Cells showing no sign were not estimated, mostly because of small sample sizes and the large number of control variables. Results for 2007 are commented on in the text but not shown in the tables owing to space constraints ([98]).

5.4.1. Median income

Median income is clearly lowered by foreign-born populations across Europe. A marginal increase in foreign-born residents – holding the income of immigrants and natives constant – would decrease a country's median income. Unconditional effects are larger than conditional effects, as would be expected when considering the uneven distribution of covariates such as education and household size between the native- and foreign-born. The negative effect can thus partly be attributed to these factors. However, a statistically significant negative effect persists in most countries even when controlling for observable characteristics. In fact, the only two countries in which immigrants show a positive effect on the median income are Czechia and Serbia, for the EU-born (Table 5.3). Although effect magnitudes are not reported in Tables 5.2 and 5.3 (but are available upon request from the authors), it should be mentioned that a country grouping can be observed here, and similarly across the other social indicators: The effect is generally the largest in Nordic countries, followed by the more westerly central European countries and then southern European countries. The effect tends to be small and sometimes not significantly different from zero in central and eastern European countries. The magnitude of the effects tends to be larger for non-EU-born than for EU-born households. For example, conditional IF regression results suggest that the non-EU-born households decreased Luxembourg's median annual income in 2018 by around EUR 2 400 whereas EU-born households are estimated to have decreased it by around EUR 1 700.

Table 5.2: Unconditional IF regression results on the seven social indicators, by country and by EU-born and non-EU-born population, 2018

(direction of effects and statistical significance)

Country	Birthplace	Median	Mean	Gini	AROP	SMD	QJ	AROPE
Belgium	EU	–	(–)	+	(+)	+	+	+
	Non-EU	–	–	+	+	+	+	+
Czechia	EU	(+)	(+)	+	(+)	(+)	(–)	(+)
	Non-EU	(–)	(–)	(+)	(+)	(+)	(–)	+
Denmark	EU	–	(+)	(+)	(+)	+	(+)	+
	Non-EU	–	–	(+)	+	+	+	+
Germany	All	–	–	(+)	(+)	+	(+)	+
Estonia	All	–	–	+	+	+	(–)	+
Ireland	EU	–	–	(–)	(–)	(+)	+	(+)
	Non-EU	(–)	(–)	(+)	+	(+)	+	+

([96]) Further results are available upon request.
([97]) The observable characteristics we control for are household type (number of adults and number of children) and within-household shares of persons falling into certain age groups, education groups and activity status groups.
([98]) Full results are available upon request.

Country	Birthplace	Median	Mean	Gini	AROP	SMD	QJ	AROPE
Greece	EU	–	–	+	+	+	(+)	+
	Non-EU	–	–	+	+	+	+	+
Spain	EU	–	–	+	+	(+)	(+)	+
	Non-EU	–	–	+	+	+	(+)	+
France	EU	–	–	(+)	(+)	(+)	(+)	+
	Non-EU	–	–	+	+	+	+	+
Croatia	EU	–	(–)	(+)	(–)	(+)	(+)	(+)
	Non-EU	–	–	+	+	+	(+)	+
Italy	EU	–	–	(+)	–	+	(–)	+
	Non-EU	–	–	+	(–)	+	(–)	+
Latvia	All	–	–	+	+	+	(+)	+
Lithuania	EU	(–)	(–)	(–)	(–)	(+)	–	(+)
	Non-EU	–	–	(+)	(+)	+	(–)	+
Luxembourg	EU	–	–	+	(–)	(+)	–	+
	Non-EU	–	–	+	+	+	+	+
Hungary	EU	(+)	(+)	(+)	(+)	–	(–)	(–)
	Non-EU	(–)	(+)	+	(+)	(+)	–	(+)
Netherlands	EU	–	–	+	(+)	+	+	+
	Non-EU	–	–	+	+	+	+	+
Austria	EU	–	–	+	+	+	(+)	+
	Non-EU	–	–	+	+	+	+	+
Poland	EU	(–)	(–)	(–)	(–)	(+)	–	(+)
	Non-EU	(–)	(–)	(+)	(+)	–	–	(+)
Portugal	EU	(+)	(+)	(+)	(+)	–	(+)	(–)
	Non-EU	–	(–)	(+)	(–)	+	(+)	+
Slovenia	All	–	–	+	+	+	(+)	+
Finland	EU	(–)	–	–	(–)	(+)	(+)	(+)
	Non-EU	–	–	+	(–)	+	+	+
Sweden	EU	–	–	(+)	(–)	(+)	(+)	+
	Non-EU	–	–	+	+	+	+	+
Norway	EU	–	–	(+)	(–)	(–)	(+)	+
	Non-EU	–	–	+	+	+	+	+
Serbia	EU	+	+	–	–	(+)	(–)	(–)
	Non-EU	(+)	(+)	(+)	(–)	(+)	–	(+)
Switzerland	EU	–	(–)	+	(+)	(–)	(–)	+
	Non-EU	–	–	+	+	+	+	+
United Kingdom	EU	(+)	(+)	(+)	(–)	(+)	–	(–)
	Non-EU	–	(–)	+	(+)	+	(+)	+

Note: Positive IF regression estimates are represented by a '+', negative estimates by a '–'. Statistically insignificant results are reported in brackets. Iceland and Slovakia are not covered in the 2018 EU-SILC.

Reading note: In Belgium, both EU-born and non-EU-born immigrants have a negative impact on median income without controlling for differences in household characteristics between immigrant and native households. This means that a marginal increase in foreign-born residents – holding the income of immigrants and natives constant – would lower Belgium's median income.

Source: Authors' computations, UDB September 2019.

Table 5.3: Conditional IF regression results by country and by EU-born and non-EU-born immigrant population, 2018
(direction of effects and statistical significance)

Country	Birthplace	Median	Mean	Gini	AROP	SMD	QJ	AROPE
Belgium	EU	–	(–)	+	(+)	(–)	(–)	+
	Non-EU	–	–	+	(–)	(+)	(–)	+
Czechia	EU	+	+	(+)	(+)	(–)	(+)	(–)
	Non-EU	–	–	(+)	(+)	(+)	(–)	+
Denmark	EU	–	(+)	(+)	(+)	(+)	(–)	+
	Non-EU	–	–	(+)	(+)	+	(–)	+
Germany	All	–	(–)	(+)	(+)	(+)	(–)	+
Estonia	All	–	–	(+)	(+)	(+)	(–)	+
Ireland	EU	–	–	(–)	(–)	(+)	+	+
	Non-EU	(–)	(+)	(+)	(+)	(+)	(+)	+
Greece	EU	–	–	+	+	+	(+)	+
	Non-EU	–	–	+	(–)	+	(–)	+
Spain	EU	–	–	+	+	+	(–)	+
	Non-EU	–	–	+	+	+	(+)	+
France	EU	–	–	(+)	(+)	(+)	(–)	+
	Non-EU	–	–	+	+	+	(+)	+
Croatia	EU	(+)	(+)	–	(–)	(+)	(–)	(–)
	Non-EU	(–)	(–)	(+)	(–)	(–)	(–)	(+)
Italy	EU	–	–	(+)	–	(+)	(–)	(+)
	Non-EU	–	–	+	(+)	+	(–)	+
Latvia	All	(–)	(–)	(+)	(–)	–	(+)	(+)
Lithuania	EU	(+)	(+)	(–)	(–)	(–)	(–)	(–)
	Non-EU	(–)	–	–	(–)	+	(–)	(+)
Luxembourg	EU	–	–	+	–	(+)	(–)	+
	Non-EU	–	–	+	(+)	+	(+)	+
Hungary	EU	(+)	+	(+)	(+)	–	(–)	(–)
	Non-EU	(–)	(+)	+	(+)	(+)	(–)	(+)
Netherlands	EU	(+)	(–)	(+)	(+)	(+)	(–)	+
	Non-EU	–	–	(+)	+	+	+	+
Austria	EU	–	–	+	(+)	+	(–)	+
	Non-EU	–	–	+	(+)	(+)	(–)	+
Poland	EU	(+)	(+)	(–)	(–)	(+)	–	(–)
	Non-EU	(–)	(–)	(+)	(+)	–	(–)	(+)
Portugal	EU	(–)	(+)	(–)	–	–	–	–
	Non-EU	–	(–)	(+)	(–)	+	(+)	+
Slovenia	All	–	–	+	(+)	(+)	–	+
Finland	EU	(–)	–	–	(+)	(+)	(–)	(+)
	Non-EU	–	–	(–)	(–)	(+)	(+)	(+)
Sweden	EU	–	–	(+)	(–)	(+)	(+)	(+)
	Non-EU	–	–	+	+	(+)	(+)	+
Norway	EU	–	–	(+)	(–)	(+)	(–)	(+)
	Non-EU	–	–	(+)	(–)	+	(+)	+

Country	Birthplace	Median	Mean	Gini	AROP	SMD	QJ	AROPE
Serbia	EU	+	(+)	–	(–)	(–)	(+)	(–)
	Non-EU	(+)	(+)	(+)	(–)	(+)	(–)	(+)
Switzerland	EU	–	(–)	+	(–)	(–)	–	+
	Non-EU	–	–	(+)	(–)	(+)	(–)	(+)
United Kingdom	EU	–	(–)	(+)	(–)	(+)	–	(+)
	Non-EU	–	(–)	+	(–)	+	(–)	+

Note: Positive IF regression estimates are represented by a '+', negative estimates by a '–'. Statistically insignificant results are reported in brackets.

Iceland and Slovakia are not covered in the 2018 EU-SILC.

Reading note: Even after controlling for differences in household characteristics between foreign-born and native households, both EU-born and non-EU-born households members have a negative impact on median income in Belgium.

Source: Authors' computations, UDB September 2019.

5.4.2. Mean income

As it is for median income, the effect of the foreign-born on mean income is clearly negative across European countries. However, its magnitude is smaller overall. Fifteen countries (Austria, Belgium, Czechia, Denmark, Finland, France, Greece, Italy, Lithuania, Luxembourg, the Netherlands, Norway, Spain, Sweden and Switzerland) report a negative conditional contribution of their non-EU-born populations, and 10 countries (Austria, Finland, France, Greece, Ireland, Italy, Luxembourg, Norway, Spain and Sweden) a negative contribution of their EU-born populations to mean income. Serbia is the only country in which EU-born households are estimated to have a positive raw effect on the mean income, and Czechia and Hungary are the only countries in which the conditional effect is positive. There is no clear evidence that the conditional effects on mean income among either EU-born or non-EU-born immigrants have become systematically smaller or larger between 2007 and 2018. Nonetheless, the clearly negative marginal contribution of foreign-born populations to both the mean and median incomes reflects the fact that immigrants have a comparatively lower income than natives in the vast majority of countries, even after controlling for differences in household characteristics.

5.4.3. Gini

Overall, the marginal contribution of foreign-born residents to the Gini coefficient tends to be positive. This holds true across years and countries, although fewer countries report statistically significant effects than for mean income and median income. The positive coefficient reflects the over-representation of immigrants in the tails of countries' income distributions. As would be expected, the effect tends to be larger and more often statistically significant in the raw estimates than in the conditional results. However, looking at conditional results, we still find that there are three countries reporting significantly negative, that is, inequality-decreasing effects of their EU-born households on the Gini coefficient in 2018 (Croatia, Finland and Serbia). Six countries (Austria, Belgium, Greece, Luxembourg, Spain and Switzerland) report positive effects. For non-EU-born households, there is 1 country (Lithuania) in which their contribution is inequality-decreasing in 2018 but 10 in which it is inequality-increasing (Austria, Belgium, France, Greece, Hungary, Italy, Luxembourg, Spain, Sweden and the United Kingdom). We find no clear increase or decrease in the magnitude of effects between 2007 and 2018.

5.4.4. At risk of poverty

The contribution of immigrants to the AROP rate appears to be mixed overall, with few countries reporting any statistically significant conditional effect. There are both negative and positive effects among the EU-born but exclusively positive effects among the non-EU-born immigrants. A positive effect indicates that a marginal substitution of natives with foreign-born is expected to increase the

AROP rate. In some northern and the more westerly central European countries (Austria, Belgium, Ireland, Luxembourg, Norway and Switzerland) as well as Greece and Croatia, non-EU-born households show positive raw contributions to the AROP rate, but these effects disappear when we control for background characteristics including education, household composition and activity status. Italy and Serbia are the only two countries reporting negative raw effects for EU-born households in 2018. Italy maintains this negative effect when we control for household characteristics, and Luxembourg and Portugal reveal similar negative conditional effects.

5.4.5. Severe material deprivation

The influence of immigrants on SMD has to be interpreted in a similar way to previous indicators, even if the index is not a direct function of income. A positive estimate reveals that the foreign-born are over-represented among households suffering from SMD. Overall, the pattern resulting from our IF regressions is similar to that of the AROP rate. Results of the raw contributions in 2018 show that EU-born households in six countries display positive effects on SMD (Belgium, Denmark, Greece, Italy, the Netherlands and Austria) and two countries display negative effects (Hungary and Portugal). Poland is also the only country in which the non-EU-born population is estimated to have a negative effect on SMD. Conditional contributions of the foreign-born in 2018, both EU-born and non-EU-born, are also mostly positive. Yet a few countries still reveal negative conditional effects: Latvia (both EU-born and non-EU-born); Poland (non-EU-born); and Hungary and Portugal (EU-born).

5.4.6. (Quasi-)joblessness

Since we are controlling for activity status in our conditional analyses, the IF regression results are mostly statistically insignificant. Still, a few countries reveal significant contributions of their EU-born immigrant households to the QJ indicator, six in 2007 and five in 2018, with varying directions (positive in Ireland; negative in Poland, Portugal, Switzerland and the United Kingdom). Only the Netherlands reveals a significant (positive) contribution of its non-EU-born population to QJ in 2018. For all other countries, the effect is not significant.

5.4.7. At risk of poverty or social exclusion

Like for QJ, our conditional results control for activity status, which leaves the effects of AROPE mainly driven by AROP and SMD. The overall contribution of the foreign-born to AROPE is clearly positive. In 2018, 19 countries reported a positive raw contribution of their non-EU-born immigrants on AROPE. When we look at the conditional results of the same group, the effect is still positive in 15 countries. The group of eastern European countries stands out by displaying effects that are smaller than or statistically insignificant compared with those in most northern, western and southern European countries. The contributions, both raw and conditional, tend to be smaller for EU-born than non-EU-born households. However, even when controlled for observable characteristics, EU-born households in Austria, Belgium, Denmark, France, Greece, Ireland, Luxembourg, the Netherlands, Spain and Switzerland show significant positive effects in 2018.

5.5. Conclusion

This study exploits 2007 and 2018 EU-SILC data to present new evidence about the relative position of foreign-born households in the income distribution and their contribution to income inequality and social indicators in 28 European countries. Although our results show a large degree of variation across years, countries and indicators, a few general patterns emerge.

First, we find significant disadvantages in the position of foreign-born households relative to natives, on average. The implication of their position is that foreign-born households tend to contribute negatively to all of the evaluated indicators of poverty, inequality, exclusion and deprivation.

Second, foreign-born households are clearly a heterogeneous group. Unfortunately, EU-SILC data do not reveal detailed information about the country of origin of foreign-born residents, one potential source of variation. The best we can therefore do is to distinguish between immigrants born in another EU country and those born outside the EU. Perhaps surprisingly, the direction of the effects remains the same for both subgroups across most of our indicators. However, the (absolute) size of the effects is almost always smaller for EU-born residents, indicating a greater similarity to natives. Furthermore, controlling for household characteristics shows that the effect of EU-born residents shrinks starkly or disappears completely for most countries and indicators. This confirms that the estimated contribution of immigrants to social indicators can be largely attributed to observed differences in education, employment and household composition for those born in other EU countries. However, the effect remains largely unexplained for those born outside the EU.

Third, and interestingly from a European policy perspective, the disadvantage of EU-born foreign residents does not appear to decline between 2007 and 2018 despite a decade of EU integration. On the contrary, more countries register significant effects on median income, the AROP rate and the Gini coefficient in 2018 than in 2007, for example [99]. One potential explanation could be found in the 2008 financial crisis and its consequences, which had a particularly lasting impact on people with low incomes and generally vulnerable living conditions (Lecerf, 2016). Another reason may be found in the changing composition of foreign-born populations since 2007. However, the coarse definition of our data does not allow us to capture this.

Fourth, the results suggest a geographical pattern with roughly four country groups that is repeated across years and indicators – albeit with strong variation. First, the contributions of foreign-born residents to social indicators tend to be most noticeable, in terms of both quality (effect size, not shown in the tables) and quantity (number of countries showing an effect), in northern and the more westerly central European countries. Second come southern European countries with smaller magnitudes but still frequently significant effects, followed by Ireland and the United Kingdom. Lastly, the contributions of foreign-born people in eastern European countries are often statistically insignificant or only small.

Regarding EU-SILC as a tool to assess the income and living conditions of foreign-born populations across Europe, a few caveats should be noted. First, the sampling frame of EU-SILC is likely to systematically undercount the most vulnerable immigrant groups (e.g. persons seeking humanitarian protection). Because of that, our results could underestimate the effect of the foreign-born on social indicators. Second, although EU-SILC provides information on country of birth and citizenship, uncertainty about the nature of the immigration status of certain persons remains. This is particularly relevant in regions where national boundaries have shifted in the past, such as the Balkans. For more detailed research and policy recommendations, it would be helpful to have additional information provided in EU-SILC that identifies persons whose country of birth has changed name and/or boundaries, and people who live as national minorities abroad. Lastly, harmonising the definition of 'foreign-born' across countries and providing the exact birth country beyond the broad 'EU/non-EU/local' grouping would be of great analytical value.

The patterns revealed in this chapter should be understood within methodological limits. Our IF regression results portray a purely descriptive picture from which the causal effect of immigrants on the total income distribution should not be inferred. Our contribution is instead to carefully document where foreign-born residents stand in the distribution of income and other well-being indicators and to quantify their effect on various social indicators. From a broader viewpoint, the immigrant populations and their contribution to measures of poverty, inequality and deprivation are naturally embedded in each country's history and policy framework, which ultimately determine who comes to a country and how they work and live.

(99) Note that this finding should not be interpreted as evaluating the process of integration over time in the host country for a cohort of immigrants. Our repeated cross-sectional analysis shows changes over time in the conditions of the immigrant population, a population whose composition changes over time with each flow of new entrants and leavers.

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6 How much are people left behind in multidimensional poverty?

Elena Bárcena-Martín, Francisca García-Pardo and Salvador Pérez-Moreno (100)

6.1. Introduction

Leaving no one behind (LNOB) constitutes a central cross-cutting focus of the entire 2030 sustainable development agenda, which recognises that the dignity of the individual is fundamental and that the SDGs should be met for all nations and people and for all segments of society. Yet at the same time there is a lack of clarity regarding what LNOB really means and how to measure it, and also regarding the implications this has for the 2030 agenda and for policymaking in general.

The preamble to the Resolution on the SDGs adopted by the UN General Assembly in 2015 states as follows: 'We are resolved to free the human race from the tyranny of poverty and want and to heal and secure our planet.... As we embark on this collective journey, we pledge that no one will be left behind' (United Nations, 2015, p. 1). While numerous SDGs and targets address inequalities and the advancement of historically marginalised individuals and communities, the first SDG sets as a priority goal to 'End poverty in all its forms everywhere' (United Nations, 2015). In particular, its seven associated targets aim, among other objectives, to eradicate extreme poverty for all people everywhere, reduce at least by half the proportion of men, women and children of all ages living in poverty, and implement nationally appropriate social protection systems and measures for all, with the ultimate objective of LNOB.

The LNOB principle seems to respond to concerns that require a broader conception than poverty, addressing inequality explicitly. However, the term is ambiguous and open to interpretation. As the implementation of the 2030 agenda progresses, the key question to understand its normative effects is how the principle is interpreted. Does it focus on the worst off, who lack access to basic needs? Or does it suggest a broader agenda that combats discrimination, denial of human rights and inequality?

Klasen and Fleurbaey (2019) recognise that in practice it is not clear what we are talking about when we refer to the LNOB principle. In any event, LNOB suggests going beyond averages. Specifically, as Stuart and Samman (2017) point out, in countries where most people have attained minimum living standards, relative considerations become more important and focusing on closing gaps seems crucial. As the implementation of the sustainable development agenda is under way, it is useful to propose ways of measuring the LNOB principle to be able to monitor it better. In fact, Klasen and Fleurbaey (2019), for instance, suggest that the SDGs include indicators that allow those who have difficulties (or those who are further behind) to be monitored using a common metric in all countries.

The sustainable development agenda places inequalities in the spotlight. However, the interest in reducing inequalities is diminished by establishing certain thresholds in the SDGs, as the achievement of these thresholds is compatible with an increase in inequality. In this chapter, a proposal is made to

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quantify the extent to which individuals were left behind in the dimensions of the AROPE indicator in 2017 and changes in them compared with 2013. We thus intend to highlight the extent to which the people left behind did not benefit from this economic prosperity phase after the serious socioeconomic crisis suffered by a large part of the European population between 2008 and 2013.

The AROPE indicator was adopted by the EU in 2010 as a central target of the Europe 2020 strategy. As explained in Chapter 1, the AROPE concept is also used to define a new 2030 target. AROPE combines three facets: AROP, MSD and QJ. Combining these three distinct dimensions, AROPE simply reports the number and proportion of the population that meets any of the three criteria, so that meeting any one of them suffices for an individual to be included among those counted as poor or socially excluded.

As pointed by Fleurbaey (2019), trying to reduce poverty measured through the proportion of people below a threshold could focus on the people who are just below the poverty line, as they are easier to move up above the threshold. In this vein, we could give priority to populations that are badly off, but not the worst off. In other words, prioritising the worst off cannot be equated with fighting poverty any more than it can be identified with reducing inequality. One way to avoid this bias against the very worst off could be to construct poverty measures incorporating shortfalls from the built-in thresholds in each of the AROPE components. This way, we would give priority to the populations that stand to benefit most from the policy. These measures that are equivalent to the poverty gap compute the total amount by which the poor fall below the threshold. In effect they measure how much in total would be needed to raise every poor person to the threshold, assuming no effect of the policy on the pre-policy distribution. The poverty gap actually induces a bias against the populations that are moved above the threshold, because any additional benefit that they obtain after they pass the threshold has no influence on the poverty gap. In contrast, the populations that remain poor will have their whole benefit recorded in the reduction of the poverty gap. Moreover, prioritising the worst off through the use of poverty measures incorporating shortfalls from the built-in thresholds may potentially benefit the best off as well. This paradox, as Fleurbaey (2019) states, comes from the fact that the distribution of weights allotted to the various members of the population must feature an equality of weights for those who are not among the worst off – that is, their weights are all equal to zero. Therefore, this measure would not be sensitive to redistribution from the middle class to the best off.

It is clear that there are many analytical challenges embedded in translating the LNOB principle from policy language to quantitative assessment and the adoption of public policies. To start with, we need a precise understanding and identification of those who are left behind and to what extent, in order to move from aspirational language to implementing specific and effective actions based on equality and non-discrimination.

In order to measure the degree to which an individual is left behind in terms of multidimensional poverty according to the AROPE framework, in this chapter we make use of fuzzy logic. Fuzzy relations represent a formal means for modelling of rather non-trivial phenomena in the presence of a particular kind of indeterminacy called vagueness, such as that entailed in the LNOB principle. In our case, fuzzy logic allows us to attach to each individual a numerical value between 0 and 1 in order to represent the uncertainty of the concept LNOB. Our measure takes into account an individual's shortfalls from the 'best-performing' individuals (without considering a threshold), providing an appropriate valuation of the LNOB principle. This measure captures the extent of shortfalls, not just whether an individual falls below a threshold or not. Moreover, these shortfalls are assessed not with respect to some adequacy threshold, but instead relative to the best-performing individuals, so it does not ignore those who exceed the threshold.

Note that, as a way to measure the LNOB principle, inequality in multidimensional poverty or in its specific dimensions could obviously be assessed using a range of indicators, including the Gini coefficient, the ratio of the poorest 20 % of the distribution to the top 20 %, or the ratio of the bottom to either the mean or the median. Each of these measures would be relevant. However, they are global measures that allow the quantification of inequality but not an evaluation of the extent to which an individual is left behind, or how progress is shared among specific sectors of the population, or how far individuals with specific characteristics are being left behind. In this chapter, we focus on precisely these aspects.

In sum, the proposed measure is intended not as a substitute for the AROPE rate but as a complement, in the same way that in the statistical field averages are usually accompanied by dispersion measures to complete the information provided by the averages. In this sense, the evaluation of poverty would first assess the proportion of individuals that meets any of the three criteria, and then analyse the degree to which individuals are left behind in a country. The advantage of this measure is that it allows one to obtain a measure of inequality at individual level through the perspective of LNOB, specifically assessing how much each specific individual is left behind and allowing the disaggregation of this information to help identify who those left behind are and their sociodemographic characteristics. Identifying their characteristics may be particularly interesting from a policy viewpoint, as it may shed light on systematic disadvantages that leave, or threaten to leave, some segments of society behind in the wake of economic and social progress. This way, policymakers can take advantage of the understanding of this phenomenon to better shape and prioritise interventions to support progress among the furthest behind in European countries.

6.2. Methodology

This section briefly introduces the fuzzy methodology for the construction of a measure of 'left behind' (LB) in terms of multidimensional poverty, developed by García-Pardo, Bárcena-Martín and Pérez-Moreno (2021). We consider a three-step procedure. We first compute a fuzzy measure that captures the degree to which the individual is LB in a specific dimension of poverty, then aggregate across dimensions for each individual, and finally aggregate across individuals and provide overall data by country.

We work with the individuals of a country and with the three dimensions of the AROPE indicator (income, material deprivation and work intensity). We start by defining a fuzzy set for each dimension (whether continuous or non-continuous), and the sets of being LB in income, in material deprivation and in work intensity. We then assign a degree of belonging to each set to each individual, using a membership function ([101]) with values between 0 and 1.

We first focus on the definition of a fuzzy set (Zadeh, 1965) for a continuous dimension, such as income or work intensity. As we aim to measure the concept of being LB in a specific dimension, we propose using as the membership function the mean deprivation of an individual, introduced by Hey and Lambert (1979), divided by the average value of the dimension. That is, the value of the membership function assigned to each individual is the average of the relative shortfalls of individual achievements in a specific dimension with respect to those with better achievements, divided by the average achievement in that dimension.

It is worth noting that this membership function combines the information contained in the distribution function and the Lorenz curve in a way that is, in itself, meaningful. Moreover, the average of such individuals' shortfalls divided by the average achievement is the well-known Gini index of inequality of the individuals' achievements. Thus, for a given dimension, let us say income, the membership function represents the degree to which the individual is LB in terms of income, that is, it is the average of the shortfalls of individuals with respect to those with greater incomes divided by the average income. This way, an individual is totally LB in a dimension if the membership function assigned is 1; that is, he or she is at the bottom of the distribution. On the other hand, the individual is not

([101]) Fuzzy sets have been defined with the following membership function for individual:

$$LB_h(i) = \frac{\sum_{j=i+1}^{k}(x_j - x_i)}{k\,\eta_h} = 1 - L(F(x_i)) - \frac{x_i}{\eta_h}(1 - F(x_i)),$$

where x_i is the value of dimension *h* for individual *i*, and values are ranked in ascending order, $x_1 < x_2 < \dots < x_k$. We study *k* individuals, and η_h is the average value of *x*. *F(x)* is the distribution function and *(L(F(x))* is the value of the Lorenz curve for the individual *i*. This membership function provides an appropriate measure to quantify by how much the individuals are LB.

LB at all if the membership function assigned is 0; that is, he or she leads the distribution. Likewise, it should be pointed out that the extent to which individuals are LB is complementary information to the level of achievement, in the sense that, even if an individual has a low level of achievement, he or she may be at the top of the distribution. Moreover, it should be emphasised that we do not establish thresholds, or censor information. We work with all the information about individual achievements to compute the extent to which each individual is LB in each specific dimension.

On the other hand, when we work with non-continuous dimensions, we first need to focus on the transformation of non-continuous dimensions into continuous dimensions, as we intend to use the definition of a fuzzy set given above that applies to continuous dimensions. In this case, we work with material deprivation, which is composed of nine binary items. The crux of the transformation is related to the definition of a number (a score) that collects all the information about the different deprivation items considered. For this purpose, we make use of Cheli and Lemmi's (1995) proposal for each of the nine binary items. Then, the information provided by each item is weighted using a scheme that attaches more weight to the items that the population lacks the least. At the same time, that weighting penalises items that provide redundant information. Lastly, we apply the membership function described above, so that the value of the membership function represents the degree to which individual is LB in terms of the combinations of items that compose material deprivation; that is, it is the average of the shortfalls of individuals with respect to those with greater material deprivation, divided by the average.

Once we compute the extent to which each individual is LB in each specific dimension, we should combine the information across dimensions for each individual, thus permitting an unambiguous ranking of individuals in the population. With this aim, we follow the philosophy of AROPE. Hence, we take the maximum value of the degree to which an individual is LB in each of the three dimensions [102]. As result, an individual is totally LB in multidimensional poverty if the degree of LB is 1; that is, he or she is at the bottom of the ranking in any of the dimensions. An individual is not LB at all if the LB measure is 0 in all dimensions; that is, he or she leads the ranking in all dimensions. Otherwise, the degree to which an individual is LB in multidimensional poverty will be between 0 and 1.

Finally, we aggregate the degree to which individuals in one country are LB in multidimensional poverty, and provide an overall measure for each country, that is, the average of the individual LB scores, which provides information on how much citizens are LB across EU countries. We should remark that the LB measure complements the information at the level of multidimensional poverty but does not replace it. In this line, we could use the LB measure to complement information on the AROPE indicator or, for instance, on other eventual measures based on Alkire and Foster's (2011a,b) methodology. The LB measure is a measure of inequality at individual level from the perspective of the LNOB principle that specifically assesses how much each specific individual is LB, and allows the disaggregation of this information to help identify sociodemographic characteristics of those farthest behind.

(102) Note that there is more than one way to formulate a composite indicator of multidimensional poverty under a fuzzy-set approach. In this work, the aggregation at the individual level of the LB score across the three dimensions uses the union of fuzzy sets (following the logic of AROPE). Results depend on the aggregation at the individual level of the LB score across the three dimensions. We refer the reader to Garcia-Pardo et al. (2020) for a robustness check of different alternatives of aggregation. Obviously, results are also sensitive to the membership function chosen and to the aggregation of the individual LB scores at the country level. These robustness checks are out of the scope of this work, and have been left for a more elaborate analysis in the future.

6.3. Measuring the extent to which individuals are left behind in multidimensional poverty across European countries

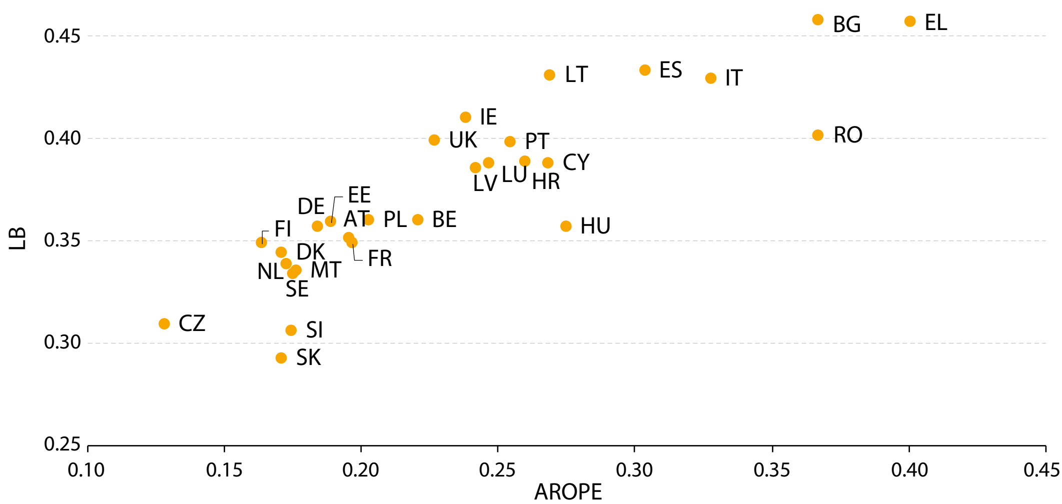
To start with, we assess the extent to which individuals are LB in multidimensional poverty in 28 European countries (27 Member States and the United Kingdom) based on the EU-SILC 2017 data set. In particular, we use our fuzzy approach to identify those who are farther away from the best-positioned individuals and to gauge how far behind them they are, providing country-level LB measures.

We consider multidimensional poverty on the basis of the three indicators contained in the AROPE rate. Although, as we all know, this measure is limited, we rely on the rich literature that justifies the EU-SILC indicators (Atkinson and Marlier, 2010), and attempt to take advantage of them to measure the LNOB principle in terms of multidimensional poverty across European countries.

We choose the individual as unit of analysis essentially because social rights tend to be recognised for individuals in the European legal framework.

The AROPE rate ([103]) and the average measure of LB for 2017 for each country are reported in Figure 6.1. This illustrates that the two measures are positively correlated. Hence, unsurprisingly, at first glance countries with a greater AROPE rate also have a greater average level of the LB measure. In other words, these countries not only have a greater proportion of AROPE individuals, but also leave people behind to a greater extent. Thus, Pearson's and Spearman's correlation coefficients between the AROPE rate and the LB measure are high, positive and significant.

Figure 6.1: AROPE rate and LB measure, 2017



Note: See Appendix 2 for a list of country abbreviations. Correlation = 0.88; Spearman ranking coefficient = 0.89.

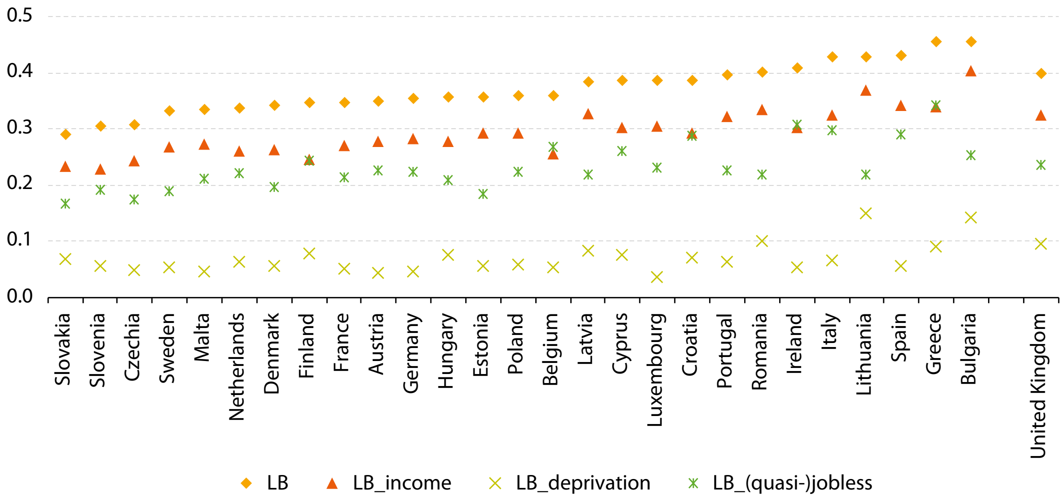
Reading note: Slovakia has 17.1 % of individuals AROPE and its degree of the LB measure is 0.29.

Source: Authors' computations, UDB 2017-3.

([103]) We adopt a rigorous approach to the treatment of missing values, dropping respondents who have a missing value in any indicator (less than 0.13 % of the sample) and using sample weights.

Aside from the general correlation between the AROPE rate and the LB measure, some specific points should be stressed. First, as explained above, the greater the LB measure is, and the closer to 1, the more pressing is the problem of leaving people behind. Therefore, the problem is especially significant in Bulgaria, Greece, Spain, Lithuania and Italy. Second, the correspondence between AROPE and LB is far from perfect, as each provides information about different aspects of multidimensional poverty. While the AROPE rate describes how many people suffer from multidimensional poverty, the LB measure allows us to evaluate on average how far people are LB in terms of multidimensional poverty. Finland, the United Kingdom and Ireland, which rank 2nd, 15th and 16th, respectively, in ascending rank of the AROPE indicator, climb at least six positions in the LB ascending ranking. That is to say that, in these countries, the proportion of AROPE people is not as great as the extent to which people are falling behind, highlighting that there is a significant problem of socioeconomic inequality aside from the incidence of multidimensional poverty. In contrast, in Hungary, even though the AROPE rate is high (ranking 23 out of 28), the problem of leaving people behind is not as pressing as in countries with lower AROPE rates. Third, we can also measure the degree of being LB in each dimension (see Figure 6.2) ([104]). In general, in most countries the problem of leaving people behind is highest in the income dimension, followed by work intensity, while its extent is lowest for material deprivation. However, it varies considerably across countries, and there are even exceptions, such as Belgium and Ireland, where the problem of leaving people behind is slightly greater in work intensity than in income.

Figure 6.2: The LB measure by dimensions, 2017



Note: Countries ranked in ascending order of overall LB measure.

Reading note: Slovakia's average measure of LB in multidimensional poverty is 0.29, while its average measure of LB is 0.24 in income, 0.07 in material deprivation and 0.17 in work intensity.

Source: Authors' computations, UDB 2017-3.

([104]) Notice that the ranking of countries differs depending on the dimension analysed, and that there is no additive decomposition by dimension, as the degree of the LB measure in multidimensional poverty for a country is the average of the maximum level of LB for each individual.

6.4. How left-behind individuals have progressed, across European countries

In this section, we describe the change in the overall LB measure by country in 2013–2017 as a way of assessing the extent to which progress has been widely distributed and has reached the least favoured individuals of the population.

Table 6.1 compares the LB measure in multidimensional poverty in 2013 and 2017 for each country. While 15 countries significantly reduced the degree to which people were LB – the most prominent reductions are in Ireland and Hungary – only two countries (Luxembourg and the Netherlands) significantly increased their LB measures.

It is worth comparing the change in mean values of the LB measure for the overall population (overall) of each country and the change in the mean values of the LB measure for a population group that falls in the upper part of the LB distribution (the 40 % who are most LB). This way, we can assess how changes in the degree of being LB are distributed within each country. If we compare overall change in the LB measure with the change for the 40 % of those most LB, we can conclude that changes have been shared progressively if increases are smaller for the 40 % of individuals most LB than in the overall distribution, or if decreases have been greater for those most LB.

We can spot different types of progress in Table 6.1. First, there are 15 countries in which the overall LB measure significantly decreases, and in 10 countries the most LB people have benefited in greater proportion from the reduction in LB. The most remarkable reductions in overall LB are for Ireland and Hungary. The reduction of those most LB in Hungary is lower than the overall reduction, while in Ireland the opposite takes place. Ireland significantly reduces its overall measure of LB, and the reduction for those most LB is greater than the overall reduction, providing evidence that this improvement is progressively distributed, since those further away from the lead decreased their LB measure more than the overall mean. Finally, Bulgaria and Austria significantly increase their LB measure, even though those farther from the lead are harmed less than those who are farther ahead; in other words, the change was progressive. Only Luxembourg shows a significant increment in the degree to which individuals are LB accompanied by an increment of those most LB that is greater than the increment of the best-positioned individuals.

An analysis of the change in the degree to which individuals are LB in each individual dimension is reported in Table 6.2. This time, we compare the change in the LB measure in each dimension with the change for the 40 % of those most LB in each dimension.

Table 6.2 shows that 14 countries reduced their measures of LB in income, although only 4 significantly. In other words, in most of the countries people were LB in the income dimension on average at least as much in 2017 as in 2013. Moreover, changes in the LB measure in income, either increases or decreases, were progressively shared, so that those most LB benefited the most from the changes in six countries (Greece, Latvia, Malta, Poland, Portugal and Slovakia). For material deprivation, 15 countries significantly reduced the degree to which individuals were LB, and in 12 the most LB benefited more intensively from changes, either increases or decreases. The increase in LB in deprivation in Lithuania, the Netherlands, Finland, Sweden and the United Kingdom especially harmed the most LB. Finally, the extent to which individuals are LB in terms of work intensity decreased in 21 countries (16 significantly), even though changes, either increases or decreases, were distributed progressively in 18 countries. Spain, Croatia, Hungary and Slovakia show very progressive reductions in the extent to which individuals were LB in terms of work intensity. In sum, all this confirms that, even though changes in multidimensional poverty highlight some trends, they differ significantly across countries and dimensions, with our approach providing valuable information about the progress made by country and dimension in terms of the LNOB principle.

Table 6.1: LB measures, 2013 and 2017

Country	LB 2013	LB 2017	Change in LB 2017-2013	
			Overall	Top 40 %
Belgium	0.36	0.36	0.00	−0.01
Bulgaria	0.43	0.46	0.03 (*)	0.02
Czechia	0.33	0.31	−0.02 (*)	−0.03
Denmark	0.35	0.34	−0.01 (*)	−0.03
Germany	0.37	0.36	−0.02	−0.01
Estonia	0.39	0.36	−0.03 (*)	0.01
Ireland	0.46	0.41	−0.05 (*)	−0.11
Greece	0.48	0.46	−0.02 (*)	−0.05
Spain	0.44	0.43	−0.01 (*)	−0.01
France	0.37	0.35	−0.02 (*)	−0.01
Croatia	0.42	0.39	−0.03 (*)	−0.04
Italy	0.42	0.43	0.01	0.02
Cyprus	0.39	0.39	0.00	0.01
Latvia	0.42	0.39	−0.03 (*)	−0.04
Lithuania	0.42	0.43	0.01	0.01
Luxembourg	0.37	0.39	0.02 (*)	0.03
Hungary	0.40	0.36	−0.05 (*)	−0.02
Malta	0.36	0.34	−0.02 (*)	−0.05
Netherlands	0.33	0.34	0.01 (*)	0.01
Austria	0.35	0.35	0.00 (*)	−0.04
Poland	0.38	0.36	−0.02 (*)	−0.01
Portugal	0.43	0.40	−0.03 (*)	−0.03
Romania	0.43	0.40	−0.03 (*)	−0.03
Slovenia	0.33	0.31	−0.02 (*)	−0.04
Slovakia	0.34	0.29	−0.04	−0.06
Finland	0.33	0.35	0.02	0.03
Sweden	0.32	0.33	0.01	0.00
United Kingdom	0.40	0.40	0.00	−0.04

Note: Top 40 % refers to the change in the LB measure for the 40 % most LB. (*) Significant overall change in the LB measure with 95 % confidence.

Reading note: On average, in Bulgaria individuals are LB in multidimensional poverty by 0.43 in 2013 and by 0.46 in 2017. Between 2013 and 2017, there is a significant increase of 0.03 points in the degree to which individuals are LB. The change in the LB measure for those in the top 40 % of the LB is 0.02, smaller than the overall change. Therefore, those most LB have been less damaged by the increase in terms of the LB measure; that is, this change has been shared progressively.

Source: Authors' computations, UDB 2017-3.

Table 6.2: Changes in the LB measure by dimension, 2013–2017

Country	Income		Deprivation		Work intensity	
	Overall	Top 40 %	Overall	Top 40 %	Overall	Top 40 %
Belgium	0.00 (*)	0.01	0.00	0.00	0.00	−0.01
Bulgaria	0.05 (*)	0.06	−0.01 (*)	−0.02	−0.03	−0.02
Czechia	−0.01	−0.01	−0.02 (*)	−0.03	−0.03 (*)	−0.05
Denmark	0.01 (*)	0.02	0.00	0.00	−0.03	−0.07
Germany	−0.01	−0.01	−0.01 (*)	−0.04	−0.02	−0.04
Estonia	−0.03	−0.03	−0.01 (*)	0.00	−0.05 (*)	−0.10
Ireland	0.00	0.00	−0.01 (*)	−0.03	−0.08 (*)	−0.16
Greece	−0.01 (*)	−0.02	0.00	0.00	−0.03 (*)	0.01
Spain	0.01	0.02	0.00	−0.06	−0.04 (*)	−0.14
France	−0.02	−0.02	−0.01 (*)	0.00	0.00	0.00
Croatia	−0.02	−0.02	−0.01 (*)	0.00	−0.04 (*)	−0.15
Italy	0.00	0.00	0.00 (*)	−0.02	0.01	0.04
Cyprus	−0.01 (*)	−0.01	0.01 (*)	0.02	0.01 (*)	0.03
Latvia	−0.02	−0.03	−0.03 (*)	−0.02	−0.03 (*)	−0.06
Lithuania	0.02	0.03	0.06 (*)	0.19	−0.02 (*)	−0.03
Luxembourg	0.00 (*)	0.02	0.00	0.02	0.01 (*)	0.02
Hungary	−0.02	−0.02	−0.03 (*)	−0.06	−0.08 (*)	−0.14
Malta	0.00	−0.01	−0.03 (*)	−0.05	−0.04 (*)	−0.01
Netherlands	0.02 (*)	0.04	0.01 (*)	0.09	−0.01 (*)	−0.02
Austria	0.01	0.02	0.00 (*)	0.01	0.00	−0.01
Poland	−0.02	−0.03	−0.01 (*)	−0.03	−0.02 (*)	−0.02
Portugal	−0.01 (*)	−0.02	−0.01 (*)	−0.02	−0.06 (*)	−0.08
Romania	−0.02	−0.01	−0.03 (*)	−0.06	−0.01 (*)	−0.03
Slovenia	−0.01	−0.01	−0.01 (*)	0.01	−0.02 (*)	−0.05
Slovakia	−0.01 (*)	−0.02	−0.02 (*)	−0.05	−0.06	−0.13
Finland	0.00	0.00	0.03 (*)	0.08	0.02	0.04
Sweden	0.02	0.02	0.01 (*)	0.06	−0.01	−0.03
United Kingdom	0.02	0.02	0.02 (*)	0.10	−0.04 (*)	−0.08

Note: Top 40 % refers to the change in the LB measure for the 40 % most LB.
(*) Significant overall change in the LB measure with 95 % confidence.

Reading note: In Bulgaria the LB measure in income increases by 0.05 on average and the corresponding change for the 40% most LB in income is 0.06, meaning that the overall change has not been progressively distributed. The LB measure in material deprivation decreases by 0.01, i.e. less than that of the 40% most LB in the deprivation dimension (0.02), meaning that the most LB have benefited more from the reduction in material deprivation than the average population.

Source: Authors' computations, UDB 2017-3.

6.5. Who is most left behind?

Let us try to answer two questions. First, to what extent are individuals with certain characteristics significantly LB in each country? Second, which are the more prevalent characteristics of those most LB in each country? The answers to both questions may provide useful and complementary information about the relative importance of different characteristics of people suffering from being LB.

To answer the first question, we compute the mean level of the overall LB measure for different sociodemographic groups in order to identify potential significant differences ([105]). In computing the LB measure, we collect data at household level and attach the household's LB measure to each member of the household. This way of proceeding assumes that resources are equally shared among members of the households, and does not consider intra-household disparities. This might not be a problem for indicators of material deprivation (which arguably do not vary across household members), but it is a problem for income, which gets divided up among members. In the absence of individual-level poverty data, we look at what can we learn assuming shared positive (or negative) effects of achieving (or not achieving) certain outcomes. Breaking down the LB score by personal characteristics (gender, age, education) may be regarded, therefore, as a limitation, as all members of the household are assigned the same level of LB score, and intra-household disparities are ignored, even though we can consider the results a lower benchmark ([106]). In this study we show that, even with the existing constraints, there is still much to be learned.

The second question focuses the attention on those most LB. In our case, we select the 20 % of individuals with the highest measure of LB and analyse the composition of the group; that is, we estimate what proportion of individuals in this group presents a given characteristic, and compare this proportion with the overall proportion of individuals with the same characteristic in each country ([107]).

6.5.1. Being left behind by sociodemographic characteristics

We now analyse the average degree to which women and men are LB in order to introduce a gender perspective. As our measure of LB is built on household-based dimensions, and most households are composed of adult men and women, we do not expect significant gender differences in the degree to which individuals are LB. Our expectation is confirmed in Figure 6.3, where mean values of the LB measure for women are slightly but not significantly greater than for men. Exceptions of countries with a significant difference are Czechia, Germany and the United Kingdom, where women are significantly more LB than men. Czechia stands out because of its significant difference by gender despite its low level of LB compared with the other countries. That is, even though the population as a whole does not fall far behind, in relative terms there are significant differences by gender with respect to other countries.

We may expect that the degree to which individuals are LB notably differs by age, as shown in Figure 6.4. Individuals are broken down into four groups: under 18, between 18 and 25, between 25 and 60, and 60 or over ([108]). Overall, the oldest group is the most LB, while those between 25 and 59 are the least LB. Differences are not always significant, but this order exists in almost all countries. Striking cases are, for instance, Cyprus and Slovenia, where older individuals are significantly more LB than the rest of individuals, whereas in Slovakia children are clearly the most LB.

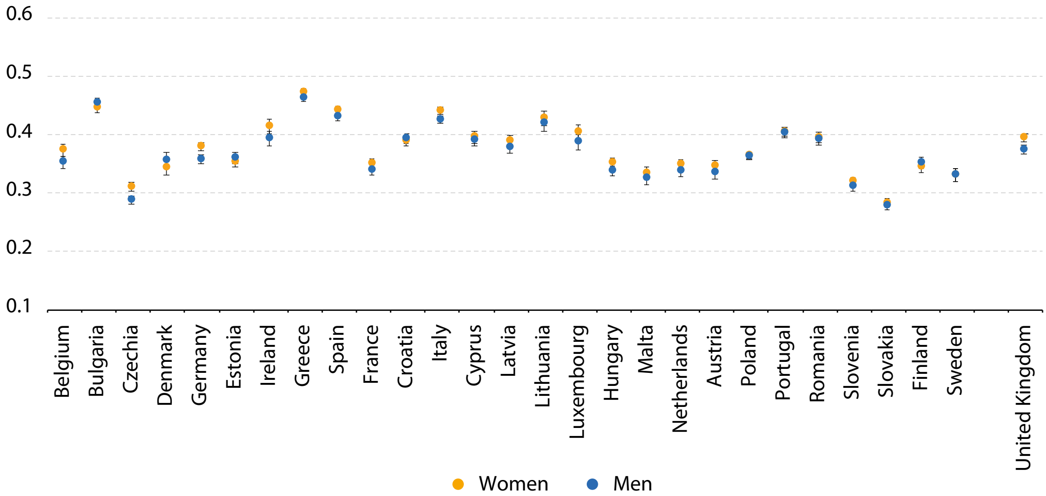
([105]) In the analysis of sociodemographic characteristics, we restrict our sample to individuals 16 years old and over, as some variables are not provided for younger individuals.

([106]) We could have compared LB measures for different sociodemographic characteristics of the household head, but this option is not without problems as, for example, numerous women live in male-headed households, including many of them who are deprived in specific ways.

([107]) This analysis is undertaken at country level to facilitate national policy design and for the sake of comparability across countries. However, this analysis could have been taken for the pool of countries to see where the people identified as being more LB live, or what proportion of those more LB belongs to each country. Both analyses are out of our scope.

([108]) Age is measured at the end of the income reference year.

Figure 6.3: LB measure by gender, 2017

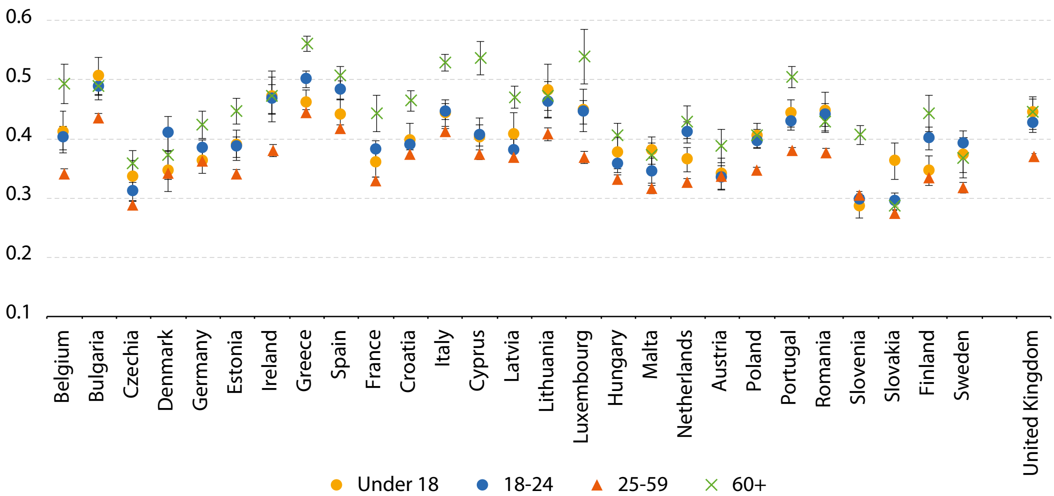


Note: 95 % confidence intervals of the average.

Reading note: In Belgium women are slightly more LB than men, even though there is no statistically significant difference, whereas in Germany women are significantly more LB than men.

Source: Authors' computations, UDB 2017-3.

Figure 6.4: LB measure by age, 2017



Note: 95 % confidence intervals of the average.

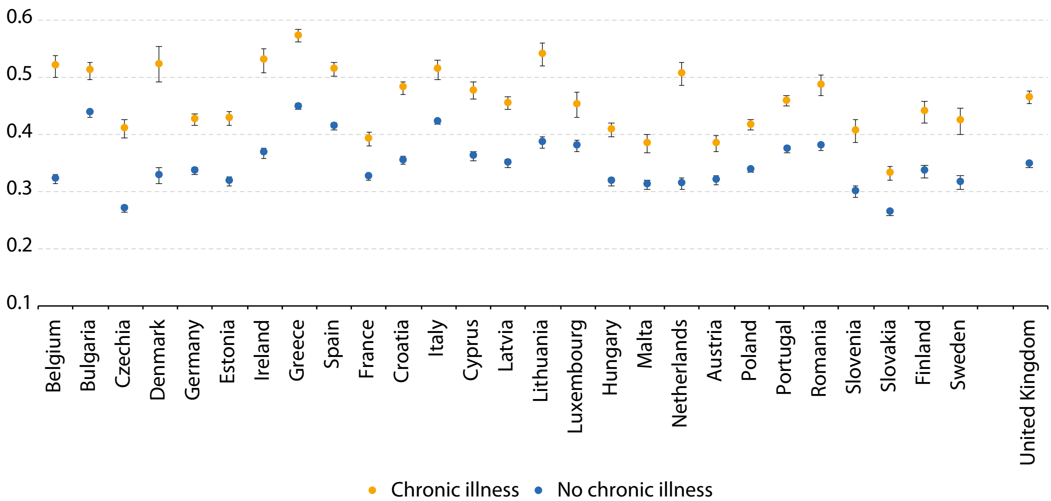
Reading note: Individuals aged 60 or over in Belgium are more LB than individuals under 18 years of age, who are more LB than individuals aged 18–24. Finally, 25–59 years of age is the least LB group. Differences are not always statistically significant.

Source: Authors' computations, UDB 2017-3.

Health limitations are also a crucial determinant when it comes to falling behind (see Figure 6.5). People who suffer from a chronic illness or condition are significantly more LB than persons without these limitations. Figure 6.5 shows that in Belgium, Denmark and the Netherlands health in particular has the greatest differential effect, while in France and Austria, although health is decisive for being LB, it has less impact than in other countries. It should be noted that Denmark is a particularly striking case, as it shows one of the highest values of the LB measure for people who are chronically ill and one of the lowest for those who are not, the difference between the two groups being one of the largest.

Education is an effective way of avoiding being LB. Individuals with high levels of educational attainment (tertiary education) are significantly less far behind than those with low educational attainment (lower than tertiary education). Our findings confirm that educational attainment has a considerable impact on the degree to which individuals are LB, even though the intensity of the effect differs among countries. For instance (see Figure 6.6), in Sweden and Denmark education makes the least difference, whereas in Romania and Bulgaria it makes the greatest difference. This is probably associated with the prevalence of highly educated people in a country (the higher it is, the lower the educational effect) ([109]). Notice also that in Greece the mean in the degree of being LB by educational attainment is the greatest for both high and low education levels.

Figure 6.5: LB measure by heath status, 2017



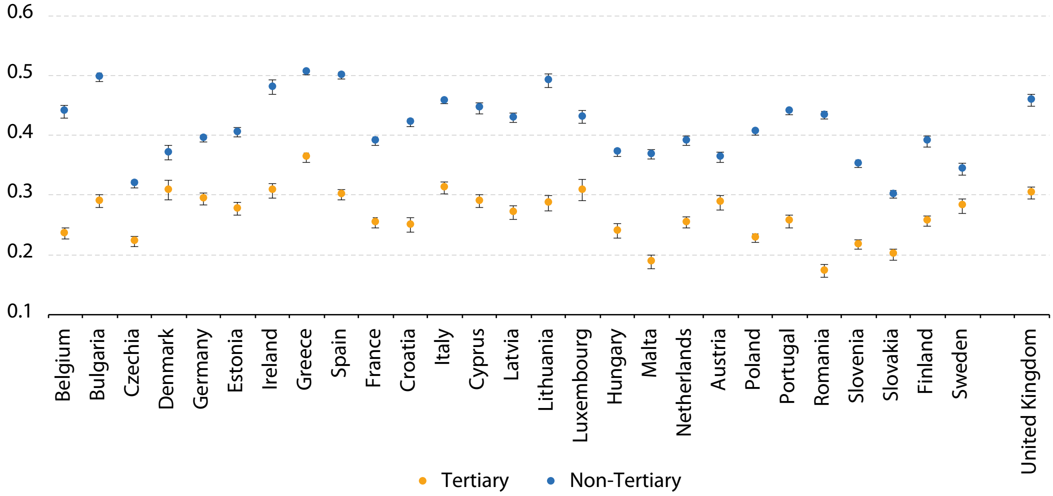
Note: 95 % confidence intervals of the average.

Reading note: Individuals who suffer from chronic illness in Belgium are more LB (0.52) than those without chronic illness (0.32) and differences are statistically significant.

Source: Authors' computations, UDB 2017-3.

([109]) This comparison between countries must also be taken with caution, as the household composition by education level may be very different across EU countries.

Figure 6.6: LB measure by educational attainment, 2017



Note: 95 % confidence intervals of the average.

Reading note: Individuals with high educational attainment in Belgium are less LB (0.24) than those with low educational attainment (0.44) and differences are statistically significant.

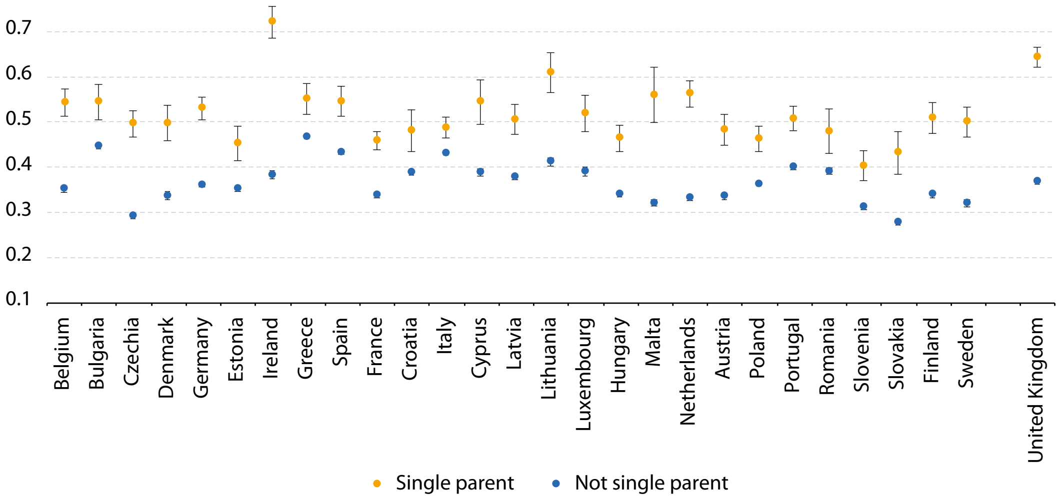
Source: Authors' computations, UDB 2017-3.

A specifically vulnerable group is individuals living in single-parent households. This vulnerability is particularly high in Ireland and the United Kingdom (see Figure 6.7), where the differential effect with respect to individuals living in other families are the greatest. On the other hand, individuals living in single-parent households in Slovenia are the least LB in comparison with single-parent households in other countries and in Greece they are the most LB.

Finally, immigrants ([110]) are also a vulnerable group in almost all countries, being significantly more LB than natives (Figure 6.8). We should be cautious in interpreting these results, given the limitations in the coverage of migrant populations. By design, EU-SILC targets the whole resident population and not specifically migrants. Furthermore, we should be even more cautious with respect to EU Member States with very low migrant populations. With these reservations, the results demonstrate that there are 10 countries (Bulgaria, Czechia, Ireland, Lithuania, Hungary, Poland, Portugal, Romania, Slovakia and the United Kingdom) with no significant differences between migrants and natives in the degree to which individuals are LB. In the other countries, natives are less far behind than immigrants, with the biggest differences in Sweden and Belgium.

([110]) Immigrants are defined as persons born in a country other than their current country of residence.

Figure 6.7: LB measure for single parents, 2017

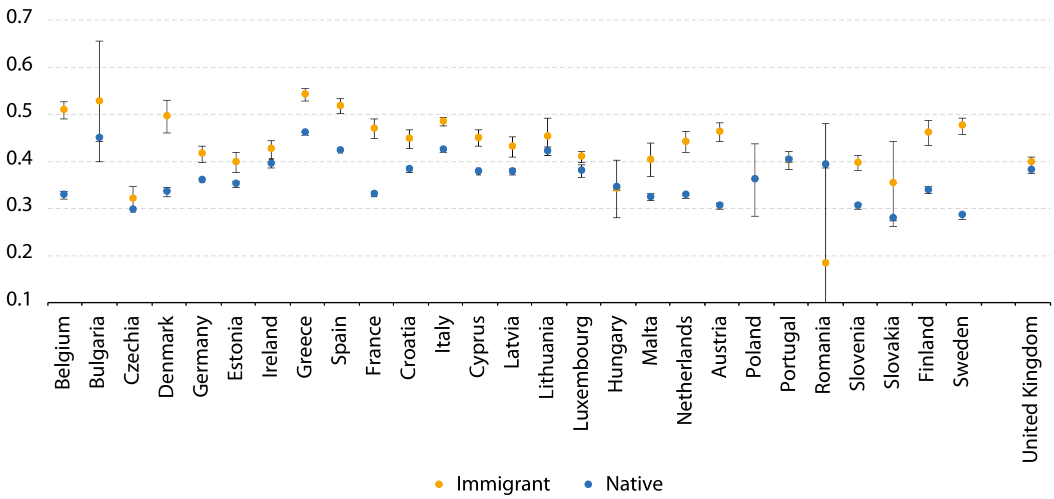


Note: 95 % confidence intervals of the average.

Reading note: Individuals living in single-parent households in Belgium are more LB (0.54) than other individuals (0.35), and differences are statistically significant.

Source: Authors' computations, UDB 2017-3.

Figure 6.8: LB measure for immigrants, 2017



Note: 95 % confidence intervals of the average.

Reading note: Immigrants in Belgium are more LB (0.51) than natives (0.33), and differences are statistically significant.

Source: Authors' computations, UDB 2017-3.

6.5.2. Prominent features among those left behind

In order to characterise the individuals most LB in each country, we compare the prevalence of a certain characteristic in the population with its prevalence among the 20 % of individuals most LB. If the prevalence is higher among the most LB, we can conclude that this is a prominent feature among those LB.

Table 6.3 shows the percentage of individuals in the overall population (O) and among the top 20 % of LB individuals (20 %), as well as the ratio between these two figures (P), which displays a value greater than 1 if the prevalence of the characteristic is greater among the most LB than in the overall population. We show that the most prominent features of those LB include suffering from chronic illness (in 28 out of 28 countries), living in a single-parent household (also in all countries) and being 60 or over (in 27 countries). Those most LB are also commonly immigrants (in 23 countries), women (19 countries) and/or young (18 countries).

It is worth underlining that Lithuania and Slovakia stand out for their high prevalence of children among those most LB, while Cyprus and Luxembourg stand out for the high prevalence of older individuals. Belgium and Ireland have notable prevalence of individuals with chronic illness, whereas in Denmark and Sweden immigrants are the most prevalent among those LB. Lastly, Czechia, Ireland, Malta, Slovakia and the United Kingdom show a prevalence of 2.4 of individuals living in single-parent households.

Obviously, each territory has its particularities, and a more detailed study of the most LB by country and region would help policymakers focus on certain socioeconomic profiles in order to reduce the distance of those most LB with respect to their surrounding societies.

Table 6.3: Percentage of individuals by characteristics in the population and among the top 20 % of individuals left behind, 2017

Country	Woman			Age 0–17			Age 18–24			Age 25–60			Age 60 and over			Chronic illness			High education			Single parent			Immigrant		
	O	20 %	P	O	20 %	P	O	20 %	P	O	20 %	P	O	20 %	P	O	20 %	P	O	20 %	P	O	20 %	P	O	20 %	P
Belgium	0.49	0.51	1.04	0.04	0.04	1.05	0.13	0.13	1.04	0.76	0.69	0.91	0.07	0.13	1.86	0.21	0.39	1.88	0.37	0.16	0.42	0.06	0.11	1.92	0.19	0.33	1.74
Bulgaria	0.50	0.48	0.97	0.03	0.04	1.37	0.10	0.12	1.28	0.74	0.68	0.92	0.13	0.16	1.17	0.18	0.24	1.36	0.23	0.05	0.23	0.03	0.04	1.55	0.01	0.01	1.61
Czechia	0.49	0.54	1.09	0.03	0.04	1.42	0.10	0.12	1.20	0.77	0.71	0.92	0.09	0.12	1.32	0.26	0.45	1.71	0.20	0.09	0.45	0.04	0.11	2.98	0.04	0.05	1.24
Denmark	0.48	0.45	0.94	0.05	0.04	0.77	0.10	0.13	1.29	0.81	0.78	0.97	0.04	0.04	1.25	0.28	0.49	1.74	0.38	0.33	0.87	0.08	0.14	1.75	0.09	0.19	2.03
Germany	0.49	0.53	1.07	0.04	0.04	0.85	0.11	0.12	1.10	0.79	0.76	0.96	0.06	0.08	1.46	0.37	0.51	1.39	0.26	0.17	0.68	0.05	0.09	2.05	0.16	0.19	1.22
Estonia	0.51	0.49	0.96	0.03	0.03	1.13	0.11	0.13	1.23	0.77	0.70	0.91	0.09	0.13	1.44	0.35	0.49	1.41	0.38	0.22	0.59	0.04	0.06	1.66	0.10	0.11	1.13
Ireland	0.50	0.54	1.07	0.05	0.07	1.24	0.13	0.17	1.26	0.74	0.65	0.88	0.08	0.12	1.52	0.23	0.40	1.77	0.44	0.26	0.59	0.06	0.18	2.88	0.21	0.21	0.98
Greece	0.50	0.51	1.03	0.03	0.02	0.74	0.09	0.08	0.95	0.73	0.62	0.84	0.15	0.28	1.84	0.16	0.28	1.74	0.27	0.19	0.72	0.01	0.02	1.52	0.09	0.09	0.96
Spain	0.50	0.52	1.03	0.03	0.03	0.89	0.10	0.10	1.06	0.74	0.66	0.89	0.13	0.21	1.63	0.23	0.35	1.49	0.32	0.15	0.46	0.03	0.04	1.57	0.14	0.16	1.19
France	0.50	0.51	1.02	0.04	0.05	1.07	0.13	0.16	1.22	0.76	0.68	0.90	0.07	0.11	1.70	0.31	0.38	1.25	0.33	0.19	0.56	0.06	0.09	1.54	0.10	0.19	1.86
Croatia	0.50	0.49	0.98	0.03	0.03	0.95	0.12	0.09	0.81	0.69	0.63	0.91	0.16	0.24	1.54	0.29	0.45	1.53	0.18	0.08	0.47	0.02	0.03	1.43	0.11	0.15	1.36
Italy	0.50	0.51	1.02	0.03	0.02	0.76	0.10	0.09	0.88	0.73	0.62	0.85	0.14	0.27	1.91	0.09	0.13	1.56	0.17	0.10	0.59	0.03	0.04	1.14	0.13	0.11	0.81
Cyprus	0.51	0.52	1.02	0.04	0.03	0.95	0.16	0.14	0.90	0.73	0.65	0.90	0.08	0.17	2.13	0.27	0.42	1.55	0.34	0.17	0.50	0.03	0.05	1.88	0.20	0.28	1.43
Latvia	0.53	0.54	1.02	0.03	0.03	1.18	0.10	0.10	0.92	0.74	0.69	0.93	0.13	0.19	1.44	0.33	0.46	1.39	0.29	0.14	0.47	0.04	0.07	1.75	0.10	0.12	1.25
Lithuania	0.52	0.51	0.99	0.03	0.05	1.48	0.13	0.16	1.19	0.74	0.68	0.91	0.10	0.12	1.25	0.24	0.41	1.69	0.33	0.11	0.34	0.06	0.13	2.20	0.05	0.06	1.25
Luxembourg	0.50	0.51	1.03	0.04	0.05	1.32	0.14	0.16	1.14	0.75	0.63	0.85	0.08	0.16	2.03	0.23	0.32	1.41	0.31	0.17	0.57	0.04	0.08	2.03	0.51	0.53	1.04
Hungary	0.51	0.52	1.02	0.03	0.03	1.06	0.12	0.12	0.99	0.74	0.69	0.94	0.11	0.16	1.39	0.30	0.43	1.43	0.21	0.11	0.52	0.04	0.07	1.86	0.01	0.01	0.99
Malta	0.48	0.49	1.01	0.06	0.08	1.45	0.10	0.11	1.09	0.73	0.68	0.94	0.12	0.13	1.10	0.24	0.30	1.23	0.22	0.06	0.26	0.03	0.08	2.44	0.06	0.10	1.64
Netherlands	0.49	0.51	1.04	0.04	0.04	1.03	0.12	0.17	1.36	0.79	0.71	0.91	0.05	0.08	1.59	0.29	0.50	1.71	0.37	0.22	0.59	0.05	0.11	2.38	0.12	0.22	1.73
Austria	0.49	0.51	1.03	0.04	0.03	0.92	0.13	0.13	0.97	0.75	0.73	0.98	0.08	0.11	1.30	0.33	0.39	1.20	0.31	0.24	0.78	0.03	0.06	1.95	0.22	0.40	1.80
Poland	0.51	0.50	0.99	0.03	0.03	1.20	0.11	0.13	1.17	0.71	0.65	0.92	0.16	0.19	1.21	0.32	0.43	1.32	0.24	0.09	0.37	0.01	0.02	1.37	0.01	0.01	1.49
Portugal	0.52	0.51	1.00	0.03	0.04	1.15	0.11	0.12	1.07	0.73	0.63	0.86	0.13	0.22	1.68	0.35	0.46	1.31	0.20	0.09	0.43	0.04	0.06	1.57	0.08	0.08	1.02
Romania	0.50	0.50	1.00	0.04	0.05	1.32	0.10	0.12	1.12	0.72	0.66	0.91	0.14	0.17	1.27	0.13	0.20	1.52	0.15	0.03	0.16	0.02	0.02	1.02	0.00	0.00	0.00
Slovenia	0.49	0.49	1.02	0.03	0.02	0.66	0.11	0.09	0.88	0.75	0.72	0.96	0.11	0.17	1.50	0.33	0.44	1.32	0.28	0.15	0.54	0.03	0.05	1.54	0.11	0.17	1.61
Slovakia	0.50	0.50	1.01	0.03	0.04	1.61	0.12	0.13	1.16	0.72	0.69	0.96	0.14	0.13	0.95	0.25	0.32	1.31	0.20	0.10	0.47	0.02	0.05	2.64	0.01	0.01	1.43
Finland	0.49	0.47	0.97	0.04	0.03	0.74	0.11	0.14	1.26	0.79	0.73	0.92	0.06	0.10	1.77	0.40	0.54	1.36	0.36	0.20	0.56	0.05	0.09	1.77	0.07	0.12	1.57
Sweden	0.48	0.47	0.99	0.05	0.06	1.21	0.12	0.16	1.37	0.79	0.72	0.91	0.05	0.06	1.33	0.32	0.43	1.35	0.34	0.28	0.82	0.06	0.12	1.89	0.23	0.46	2.04
United Kingdom	0.50	0.53	1.05	0.03	0.04	1.30	0.13	0.16	1.19	0.77	0.71	0.92	0.07	0.10	1.40	0.32	0.49	1.52	0.44	0.23	0.53	0.06	0.15	2.49	0.18	0.21	1.12

O, overall population; 20 %, 20 % of individuals most LB; P, prevalence, 20 %/O.
Reading note: In Belgium, women represent 49 % of the overall population, but 51 % of the 20 % most LB. Therefore, the prevalence is 1.04.
Source: Authors' computations, UDB 2017-3.

6.6. Conclusions

Focusing on people at the bottom of society and on closing gaps between first- and second-class citizens is one of the major challenges that underlie the 2030 sustainable development agenda and should concern policymakers across European countries. Striving to boost economic progress should be attached to achieving higher levels of shared prosperity that improve the well-being of the whole population. This study relies on a fuzzy approach for the measurement of the LNOB principle underlying the SDGs, and examines the extent to which some individuals are LB in terms of multidimensional poverty across European countries. Taking the AROPE framework as reference, our fuzzy approach allows identification of those who are further away from the best-positioned individuals and provides country-level measures of how far individuals were LB in 2017 from a comparative European perspective. The proposed measure aims to complement the information provided by the AROPE rate. We suggest dealing with poverty by first assessing the proportion of individuals meeting any of the three criteria, and then analysing the degree to which individuals are LB. The advantage is that our measure allows one to obtain a measure of inequality at individual level through the LNOB perspective, specifically evaluating how much each specific individual is LB and allowing the disaggregation of this information to help identify who are LB and their sociodemographic characteristics.

In general, we show that those countries with higher AROPE rates also have more LB people. Nevertheless, there are individual cases that would require special attention, such as Finland, Ireland and the United Kingdom, where the problem of leaving people behind is relatively high in comparison with their levels of AROPE. Likewise, when analysing the dimensions of income, material deprivation and work intensity separately, the problem of leaving people behind, despite considerable variations across countries, tends to be the highest in the income dimension followed by work intensity, while its extent is lowest for material deprivation.

From a time perspective, our results reveal that, over the post-crisis period 2013–2017, 15 countries significantly reduced the degree to which people were LB, and the people most LB benefited in a greater proportion from economic prosperity. However, once more there are notable exceptions that should not be overlooked, such as the cases of Bulgaria and Luxembourg, with significant increases in the degree to which individuals are LB. Furthermore, the analysis of the evolution of the degree to which individuals are LB by dimension provides evidence of more frequent reductions in the levels of leaving people behind in work intensity than in material deprivation and income in most countries. Luxembourg and Finland are remarkable because they have no progressive changes in any of the dimensions.

Finally, in order to focus policymaking on specific groups of population suffering particularly from the problem of being LB, our methodological proposal quantifies the following by countries: (1) how women tend to be slightly but not significantly more LB than men; (2) how much the elderly are the most LB age group; (3) how much people with chronic illnesses or other health conditions are significantly more LB than other individuals; (4) how much educational attainment is an effective way of avoiding being LB; (5) how much living in single-parent households is associated with being LB; and (6) how much immigrants are left significantly further behind than natives.

Nonetheless, along with these general trends, our comparative country-level analysis underlines significant differences across European countries beyond the incidence of multidimensional poverty. Complementing the information on absolute levels of attainment provided by the AROPE indicator with specific measures on relative achievements at individual level, as presented in this chapter, provides more comprehensive information for political decision-making. As we have seen, the AROPE rate and the extent to which individuals are LB do not necessarily go hand in hand, so that further specific and complementary analyses of two aspects of the same phenomenon, multidimensional poverty, are required.

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Understanding the role of social transfers

7 Assessing the anti-poverty effects of social transfers: net or gross? And does it really matter?

Chrysa Leventi, Andrea Papini and Holly Sutherland ([111])

7.1. Introduction

One of the aims of social security systems, and social transfers in particular, is to redistribute income in a way that supports people in poverty. Among the three indicators that are included in the Europe 2020 AROPE target, the AROP rate after social transfers is the only one that has experienced an increase during the period from 2008 to 2018 for the whole EU (see Figure 7.1). According to Eurostat, around 85 million people were income poor after social transfers in 2018.

There are two EU indicators that are used to assess the effects of social transfers on income poverty (Social Protection Committee, 2015). These are the AROP rate before social transfers, where pensions are included in social transfers, and the AROP rate before social transfers, where pensions are excluded from social transfers and are treated as part of original income. These indicators are produced using microdata from EU-SILC and measure AROP in hypothetical situations where social transfers are supposed to be absent from a country's welfare system. They are then compared with the standard AROP after social transfers to show the effectiveness of transfers in tackling income poverty, that is, by how much income poverty is reduced in their presence. The comparison is done using the same poverty threshold, namely the one where social transfers are included in the total household income.

The effectiveness of social transfers in reducing income poverty varies widely among the EU Member States. In fact, the difference between the AROP rate before and after social transfers (excluding pensions) in 2015 varied from a maximum of 20 p.p. in Ireland to a minimum 3.9 p.p. in Romania. The average decrease across the EU-27 was about 9.1 p.p. (Eurostat, 2020). Interestingly, the pre-transfer AROP rate remained stable from 2010 to 2015 at EU-27 level, whereas the post-transfer indicator experienced a rise during the same period, suggesting a decrease in the effectiveness of social transfers in reducing income poverty. Both considerations, the heterogeneity across countries and a possible overall decrease in the anti-poverty effectiveness of social transfers over time call for a deeper investigation of the roles of different types of transfers in poverty reduction and of the indicators that are used to measure their effectiveness.

The aim of this chapter is threefold. First, we explore an alternative approach to define transfers in

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Second, exploring the impact of different types of transfers on income poverty reduction may provide a more comprehensive picture of their role (Gugushvili and Hirsch, 2014). This research aims to shed light on the poverty reduction effects of public pensions, means-tested benefits and non-means-tested benefits in both gross and net terms. Disentangling aggregate benefits into subgroups of means-tested and non-means-tested benefits can be done using EUROMOD, which simulates individual benefit components separately. This is also possible for most countries using the EU-SILC data (since the 2014 wave), as a detailed breakdown of benefits was implemented using the European system of integrated social protection statistics (ESSPROS) definitions.

Finally, this research contributes to understanding the interactions between different types of benefits in a social safety net. A usual assumption when constructing hypothetical scenarios where social transfers are set to zero is that the loss of a transfer would not be (entirely or partially) compensated for by other kinds of transfers ([112]). In practice, however, this is usually not the case. For example, means-tested benefits may compensate for the loss of non-means-tested benefits; in the absence of pensions, individuals also might become eligible for other kinds of benefits, such as social assistance. As Nelson (2004, p. 386) puts it, 'If we refrain from analysing how separate social transfers and benefits interact in the distributive process and produce certain outcomes, we are likely to end up with misleading results and mistaken conclusions about the linkages between certain social policy structures and outcomes.' Combining EUROMOD with the EU-SILC microdata, the research reported in this chapter is the first to calculate the net effects of these policy scenarios, accounting for the complex interactions within and between the tax–benefit policies as well as the heterogeneity of population characteristics.

Our analysis uses EU-SILC 2015 data and is performed for the EU-27 plus the United Kingdom. The structure of the chapter is as follows: Section 7.2 explains the methodology used in this research. Section 7.3 presents and discusses the results. Section 7.4 concludes by summarising the most important findings and policy implications of this work.

7.2. Methodology and data

7.2.1. Microsimulation model and income concepts

In this chapter, we make use of EUROMOD, which enables us to estimate the taxes and SIC paid by household members in the presence and in the absence of transfers in each Member State. This allows us to measure the contributions of both net and gross transfers to income poverty reduction in comparable manners, and to account for the interconnections that exist between the different parts

([112]) Changes in the tax–benefit system can also lead to behavioural responses. For example, making social assistance less generous might improve work incentives for some people and perhaps make employment more attractive. The standard static microsimulation approach ignores any behavioural reactions of individuals to transfer withdrawal. This is also the approach that will be followed in this analysis.

of the tax–benefit system. The model uses microdata on gross incomes, labour market status and other characteristics of the individuals and households, which it then applies to the tax and benefit rules in place in order to simulate direct taxes, SIC and entitlements to cash benefits. EUROMOD has been validated at both micro and macro levels and has been extensively used to address a wide range of economic and social policy research questions (Figari et al., 2015; Sutherland and Figari, 2013).

The underlying microdata for all countries, apart from the United Kingdom, are drawn from EU-SILC 2015. For the United Kingdom, the 2014/15 Family Resources Survey is used. In EU-SILC, detailed data on benefit receipt are not available for most EU countries, as they are aggregated by function and combined in single variables. In this study, we use EUROMOD to simulate entitlements to benefits, allowing us to simulate the specific rules that apply to each and every one of them in terms of taxation and SIC. An effort has been made to address issues such as tax evasion and benefit non-take-up in countries where these phenomena are known to be prevalent.

Simulations are carried out on the basis of the tax–benefit rules in place on 30 June of the target policy year (2015). Gross market incomes are updated from the microdata income reference period (2014) to the target period using appropriate indices (updating factors) for each income source, such as administrative or survey statistics. Information on income components that cannot be calculated by EUROMOD (such as most pensions) is taken directly from the data and updated to 2015, along with market incomes ([113]).

Our analysis is in terms of equivalised household disposable income, the official income measure used when assessing income poverty and studying income distribution in general at EU level. In EUROMOD, individual disposable income is defined as market incomes plus regular inter-household cash transfers plus pensions plus benefits minus social insurance contributions minus taxes on income and wealth ([114]).

([113]) Detailed information on the scope of simulations, updating factors, non-take-up and tax evasion adjustments is documented in the EUROMOD country reports (see: https://euromod-web.jrc.ec.europa.eu/resources/country-reports).

7.2.2. Definition of baseline and hypothetical scenarios

In order to assess the effectiveness of different types of social transfers to reduce income poverty in both gross and net terms, we construct the following baseline and hypothetical scenarios ([115]). These are also summarised in Table 7.1.

- **Baseline.** Simulations are carried out for 2015 using EUROMOD and the standard AROP rates after social transfers are obtained for all countries (AROP_0, which is equivalent to the Eurostat indicator ilc_li02).
- **Scenario 1.** First, all gross social transfers (i.e. all simulated and non-simulated benefits and public old age and survivor pensions) of the baseline scenario are set to zero. New household disposable incomes are computed, assuming that taxes and SIC are not affected by the lack of transfers, and new AROP rates are obtained for all countries (AROP_1, which is equivalent to the Eurostat indicator ilc_li09b). The comparison with the baseline AROP (AROP_1 – AROP_0) provides the contribution of all gross transfers to poverty reduction. Then simulations are carried out for this hypothetical situation in which the values of all benefits and public pensions are set equal to zero, and new disposable incomes and AROP rates are obtained (AROP_1p); taxes and SIC are affected by the lack of transfers, as simulations are now accounting for their absence. The comparison with the baseline AROP (AROP_1p – AROP_0) provides the contribution of all net transfers to poverty reduction.

([114]) The Eurostat definition of disposable income also includes imputed income from the use of company cars.

([115]) When constructing the hypothetical scenarios in EUROMOD, an effort has been made to ensure that, in cases where the receipt of a benefit or pension is used by EUROMOD as a proxy indicator of a particular state in the simulations of other policies, the components of the policies that are related to this state are left intact. For example, if the receipt of a disability benefit (i.e. the benefit amount being greater than zero) is used as a proxy indicator of disability status in a country where disability tax credits exist, then these tax credits are maintained in all hypothetical scenarios.

- **Scenario 2.** All gross social benefits of the baseline scenario are set to zero. New household disposable incomes are computed, assuming that taxes and SIC are not affected by the lack of benefits, and new AROP rates are obtained (AROP_2, which is equivalent to the Eurostat indicator ilc_li10b). The comparison with the baseline AROP (AROP_2 – AROP_0) provides the contribution of all gross social benefits to poverty reduction. Then simulations are carried out for this hypothetical scenario in which the amounts of all social benefits are set equal to zero, and new disposable incomes and AROP rates are obtained (AROP_2p). The comparison with the baseline AROP (AROP_2p – AROP_0) provides the contribution of all net benefits (excluding pensions) to poverty reduction.
- **Scenario 3.** All gross public old age and survivors' pensions of the baseline scenario are set to zero. The new household disposable incomes are computed, assuming that taxes, SIC and means-tested benefits remain the same as in the baseline scenario, and new AROP rates are obtained for all countries (AROP_3). The comparison with the baseline AROP (AROP_3 – AROP_0) provides the contribution of all gross public old age and survivors' pensions to poverty reduction. Then EUROMOD is run for this hypothetical situation, and new disposable incomes and AROP rates are obtained (AROP_3p). The comparison with the baseline AROP (AROP_3p – AROP_0) provides the contribution of all net public old age and survivors' pensions to poverty reduction. Naturally, taxes/SIC are not the only variables affected in this scenario; in the absence of pensions, individuals might become eligible for other kinds of benefits, such as social assistance. They might also lose eligibility for some benefits, if pensions act as 'passports' for their receipt. This scenario takes all these complex policy interactions into account. Our methodology allows us to disentangle the part of poverty change that is related to policy interactions from the part related to changes in taxation. This is achieved by recalculating AROP rates after imposing the requirement that all benefits remain the same as in our baseline scenario.
- **Scenario 4.** In this scenario, all gross non-means-tested benefits are set to zero. New household disposable incomes are computed, assuming that taxes and SIC are not affected by the lack of these benefits, and new AROP rates are obtained (AROP_4). The comparison with the baseline AROP (AROP_4 – AROP_0) provides the contribution of all gross non-means-tested benefits to poverty reduction. Then simulations are carried out for this hypothetical scenario, and new disposable incomes and AROP rates are obtained (AROP_4p). The comparison with the baseline AROP (AROP_4p – AROP_0) provides the contribution of all net non-means-tested benefits to poverty reduction. Similarly to scenario 3, on top of changes in taxes and SIC, the lack of non-means-tested benefits also triggers changes in eligibility for means-tested benefits. We disentangle the poverty change due to policy interactions using the methodology described above.
- **Scenario 5.** In this final scenario, only gross means-tested benefits are set to zero. New household disposable incomes are computed, assuming that taxes and SIC are not affected by the lack of these benefits, and new AROP rates are obtained (AROP_5). The comparison with the baseline AROP (AROP_5 – AROP_0) provides the contribution of gross means-tested benefits to poverty reduction. Then simulations are carried out for this hypothetical situation, and new disposable incomes and AROP rates are obtained (AROP_5p), accounting for changes in taxes and SIC. The comparison with the baseline AROP (AROP_5p – AROP_0) provides the contribution of net means-tested benefits to poverty reduction.

Table 7.1: Summary of baseline and hypothetical scenarios

Scenarios	Social transfers set to zero	Equivalent Eurostat indicators
Baseline	None	ilc_li02b
1	Public pensions, means-tested benefits and non-means-tested benefits: in gross terms	ilc_li09b
1p	Public pensions, means-tested benefits and non-means-tested benefits: in net terms	—
2	Means-tested benefits and non-means-tested benefits: in gross terms	ilc_li10b
2p	Means-tested benefits and non-means-tested benefits: in net terms	—
3	Public pensions: in gross terms	—
3p	Public pensions: in net terms	—
4	Non-means-tested benefits: in gross terms	—
4p	Non-means-tested benefits: in net terms	—
5	Means-tested benefits: in gross terms	—
5p	Means-tested benefits: in net terms	—

Note: The table presents the baseline and hypothetical scenarios constructed in the present study, and the equivalent Eurostat indicators. A description of the equivalent Eurostat indicators can be found at https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Income_poverty_statistics&oldid=440992#At-risk-of-poverty_rate_and_threshold

All AROP rates are estimated using a poverty threshold set at 60 % of the median equivalised disposable income after social transfers of the baseline scenario. Standard errors and confidence intervals for the estimated results are calculated based on the DASP package developed by Araar and Duclos (2007), accounting for sampling weights. Given that EUROMOD uses EU-SILC as the basis for its input data, one would expect these AROP estimates to be the same, or almost the same. However, there are several reasons that the two sets of estimates are not identical. As this chapter focuses on conceptual issues, these differences – which in most countries are below 2 p.p. – fall outside the scope of analysis. Detailed explanations can be found in Tammik (2018).

7.3. Results

7.3.1. Deducting transfers in gross terms versus deducting transfers net of taxes and social insurance contributions

Table 7.2 presents the effects of both gross and net social transfers on the AROP rate. The comparison between scenario 1 (scenario 2) and the baseline provides the contribution of gross transfers including (excluding) pensions to income poverty reduction. The comparison between scenario 1p (scenario 2p) and the baseline depicts the contribution to poverty reduction of net transfers including (excluding) pensions.

As expected, the contribution of net transfers to poverty reduction is smaller than if they are considered in gross terms. On average across the EU-27 countries, gross transfers (including pensions) are estimated to reduce the AROP rate by 28.2 p.p., whereas net transfers reduce it by 26.6 p.p. The comparison of gross and net transfers in scenarios 2 and 2p in which pensions are treated as part of original incomes looks less striking; gross benefits are estimated to reduce the AROP rate by 10.5 p.p. whereas net benefits are estimated to reduce it by 9.9 p.p. on average across the EU-27. Our results suggest that taxation/SIC on public old age and survivors' pensions is much more prevalent in EU countries than taxation/SIC on social benefits and that taking (or not taking) these taxes/SIC into account makes a difference to keeping pension recipients out of poverty.

Figure 7.1 depicts the difference between AROP_1 (i.e. income poverty when deducting all transfers in gross terms) and AROP_1p (i.e. income poverty when deducting all transfers in net terms). Interestingly, there are two countries where income poverty is slightly lower when transfers are deducted in gross terms than in net: Slovakia and Lithuania. This prima facie counter-intuitive result is because setting all pensions and benefits to zero results in some individuals paying more health insurance contributions. These are the people who were previously exempt from paying these contributions because they were in receipt of some sort of social transfer. In Slovakia, for example, the government pays health insurance contributions for dependent children, pensioners, disabled persons, recipients of parental allowance, maternity benefit, sickness or carer benefits, and all those entitled to material need benefit and unemployment benefit ([116]).

The difference between AROP_1 and AROP_1p is equal or very close to zero for a number of countries, namely Bulgaria, Czechia, Hungary, Cyprus, Croatia, Malta and Romania. In Bulgaria all social transfers are non-taxable; in Czechia benefits and pensions lower than 36 times the minimum wage per year are not subject to income tax; in Hungary pensions are not taxable and only certain categories of benefits related to employment (e.g. sickness benefits, childcare and maternity allowances) are taxed; in Cyprus benefits, widow pensions and several other categories of old age pensions are also not taxable; in Croatia benefits are not taxable and pensions are subject to more generous tax allowances; in Malta most benefits and certain types of pensions, such as the Senior Citizenship Grant and Age Pension, are not taxed; in Romania social exclusion and family-/children-related allowances are not taxed and the tax allowance for pensions is also substantial ([117]). On the other hand, there are as many as 12 countries where the difference between AROP_1 and AROP_1p is higher than or very close to 2 p.p. These are Spain, France, Austria, Poland, Belgium, Slovenia, Luxembourg, Italy, the Netherlands, Sweden, Finland and Denmark. Where public pensions and benefits are taxed, the contribution of social transfers to income poverty reduction is thus significantly overestimated if these are considered in gross terms.

Figure 7.2 depicts the difference between AROP_2 (i.e. income poverty when deducting benefits other than pensions in gross terms) and AROP_2p (i.e. income poverty when these benefits are deducted in net terms). Our results suggest that in most countries the differences are close to zero. The most pronounced exceptions are the Nordic EU countries: Denmark, Finland and Sweden. There, this difference varies from a non-negligible 2.0 p.p. to 2.8 p.p. In all three countries most, if not all, social benefits are taxable and relatively generous, especially when it comes to unemployment benefits (Stovicek and Turrini, 2012). The difference is also statistically significant and 1 p.p. or higher in the Netherlands, Belgium, Italy, Slovenia and Luxembourg.

Are these differences capable of changing the ranking of countries in terms of the anti-poverty effectiveness of their monetary social provision systems? These rankings are often used at EU level for benchmarking welfare systems across EU countries. They also play an important role in the policy recommendations of other international institutions, such as the OECD. As Figures 7.3 and 7.4 show, the answer to this question is positive. The countries where gross social transfers (i.e. both pensions and benefits) achieve the smallest poverty reduction in 2015 are Latvia, Estonia, Bulgaria, Lithuania and Malta. This ranking does not change when transfers are considered in net terms. The country where social transfers achieve the biggest poverty reduction in both gross and net terms is Luxembourg. However, Finland, for example, which occupies the second-best place in terms of the income poverty reduction achieved by gross transfers, falls by two positions and becomes the fourth best when these transfers are considered in net terms. The countries that are found to improve their rankings are Slovakia (by as much as seven positions), Czechia, Cyprus, Croatia, Hungary, Greece and Ireland. The country with the biggest fall in the rankings is Sweden, which goes down by seven places. It is followed by Denmark and Italy, which fall three positions, Spain, the Netherlands and Finland, which fall two posi-

([116]) Detailed information on these policies is provided in the EUROMOD country report for Slovakia (see: https://www.euromod.ac.uk/using-euromod/country-reports).

([117]) Detailed information on these policies is provided in the EUROMOD country reports for Bulgaria, Czechia, Hungary, Cyprus, Croatia, Malta and Romania (see: https://www.euromod.ac.uk/using-euromod/country-reports).

tions, and Belgium, Germany, Poland, Portugal and the United Kingdom, which fall one position.

The change in the countries' ranking is less pronounced when only benefits are accounted for (Figure 7.4), with a maximum of three positions up or down the ranking. The countries where benefits achieve the biggest income poverty reduction when considered in gross terms are Ireland, Denmark and Finland. The picture changes when the anti-poverty effectiveness of benefits is considered in net terms; now the United Kingdom occupies 1st place, followed by Ireland and Luxembourg. Finland and Denmark occupy 4th and 5th places respectively.

Table 7.2: AROP rates, baseline and deducting social transfers in gross and net terms, EU-27 and United Kingdom, 2015
(%)

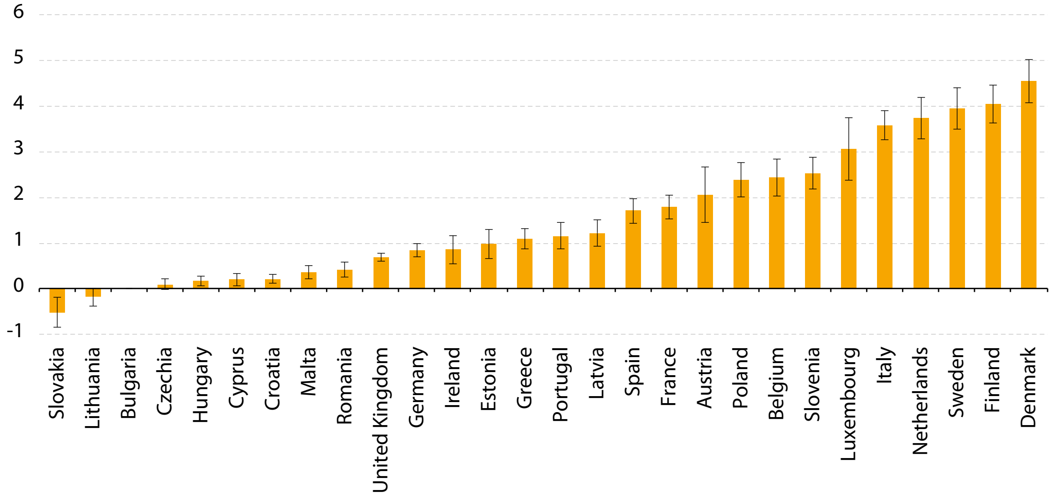
Countries	AROP_0	AROP_1	AROP_1p	AROP_2	AROP_2p
Belgium	11.1	43.8	41.3	25.3	23.8
Bulgaria	22.3	42.9	42.9	28.8	28.8
Czechia	9.1	38.4	38.3	17.9	17.9
Denmark	10.3	42.8	38.2	28.5	25.7
Germany	15.4	42.8	42	23.5	23.4
Estonia	21.2	40.5	39.6	29.1	28.3
Ireland	14.1	44.1	43.3	32.5	31.9
Greece	19.6	53.2	52.1	25.7	25.6
Spain	22.2	48.4	46.6	30.3	29.7
France	12	45.4	43.6	23.9	23.5
Croatia	19.5	44.3	44.1	30.4	30.3
Italy	18.2	49.1	45.5	27.3	26
Cyprus	14.9	40.9	40.7	28.3	28.3
Latvia	22	41.3	40.1	27.3	27.2
Lithuania	21.5	43.3	43.5	28.6	28.4
Luxembourg	9.7	46.5	43.4	26.7	25.7
Hungary	18.9	50.5	50.3	27.8	27.6
Malta	15.2	37.6	37.3	24.7	24.7
Netherlands	11.2	37.3	33.5	25.8	24.2
Austria	12.1	46.4	44.4	24.6	24.7
Poland	17.6	46.7	44.3	23.9	23.2
Portugal	19.1	46.9	45.7	26.3	26.3
Romania	23.8	50.4	49.9	30.3	30.3
Slovenia	14.4	44.3	41.7	25.6	24.6
Slovakia	11.4	37.5	38	18.3	18.9
Finland	10.5	46.5	42.5	28.8	26
Sweden	14.6	41.4	37.5	25.9	24
United Kingdom	15	41.3	40.6	33	33

Reading note: In Latvia, the baseline AROP rate is estimated to be 22 %, and the AROP rate before social transfers (pensions included in social transfers) in gross terms is 41.3 %. In net terms (i.e. taking into account the fact that taxes and SIC are affected by the lack of transfers), the AROP rate before social transfers is estimated to be 40.1 %.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.1: Comparison of the anti-poverty effects of gross and net social transfers (including pensions), EU-27 and United Kingdom, 2015

(p.p.)



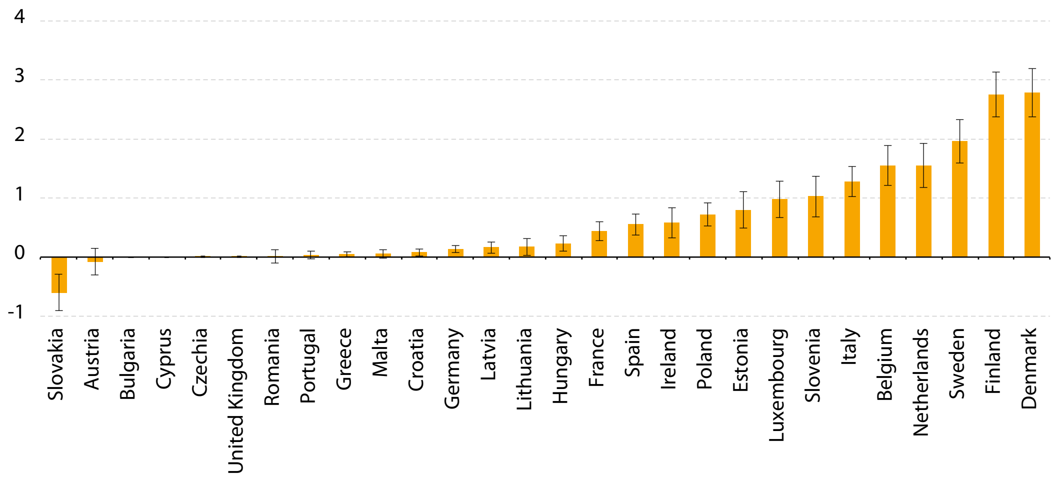
Note: Countries are ordered according to the difference between AROP_1 and AROP_1p. Standard errors for 95 % confidence intervals are calculated using DASP.

Reading note: In Ireland, the difference between the contribution of all gross transfers (including pensions) to poverty reduction and the contribution of all net transfers to poverty reduction is 0.8 p.p.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.2: Comparison of the anti-poverty effects of gross and net social transfers (excluding pensions), EU-27 and United Kingdom, 2015

(p.p.)

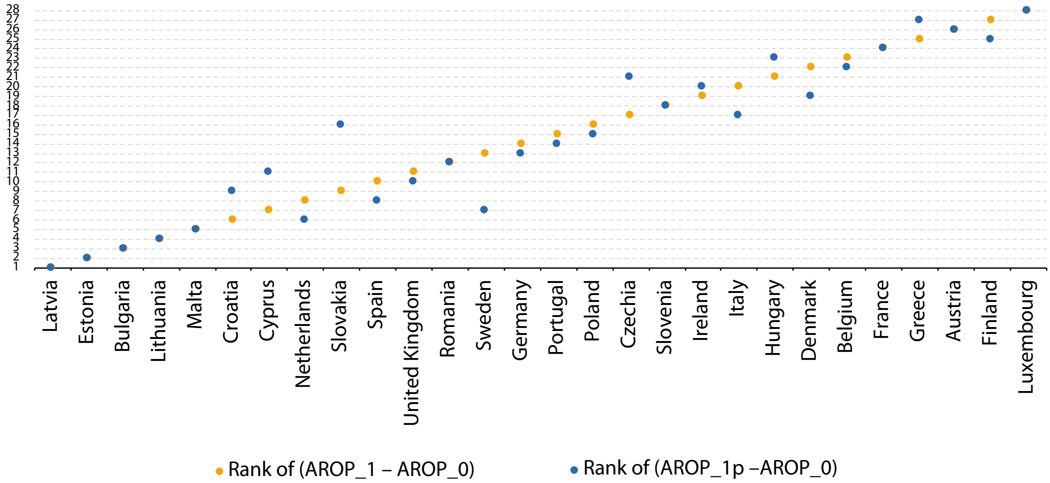


Note: Countries are ordered according to the difference between AROP_2 and AROP_2p. Standard errors for 95 % confidence intervals are calculated using DASP.

Reading note: In Belgium, the difference between the contribution of all gross social transfers (excluding pensions) to poverty reduction and the contribution of all net social transfers to poverty reduction is 1.5 p.p.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.3: Country ranking by contribution of gross and net social transfers (including pensions) to income poverty reduction, EU-27 and United Kingdom, 2015

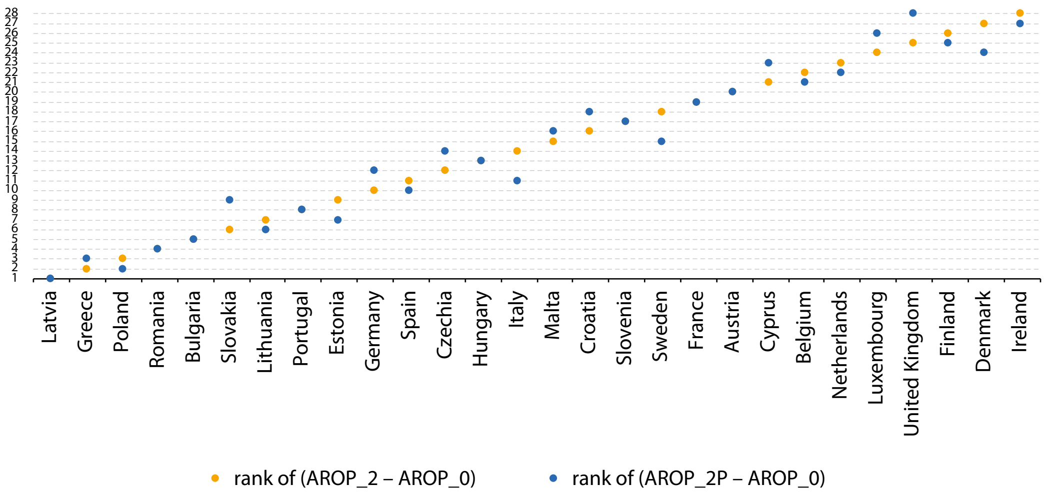


Note: Countries are ordered according to the rank of (AROP_1 – AROP_0).

Reading note: Finland occupies 2nd place in terms of income poverty reduction achieved by gross transfers (including pensions); it falls by two positions, taking 4th place, when these transfers are considered in net terms.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.4: Country ranking by contribution of gross and net social transfers (excluding pensions) to income poverty reduction, EU-27 and United Kingdom, 2015



Note: Countries are ordered according to the rank of (AROP_2 – AROP_0).

Reading note: Denmark occupies 2nd place in terms of income poverty reduction achieved by gross transfers (excluding pensions); it falls by three positions, taking 5th place, when these transfers are considered in net terms.

Source: Authors' calculations using EUROMOD Version H1.0.

7.3.2. Disentangling the effect of net/gross conversion and of social transfer interdependencies

A typical assumption when constructing scenarios in which social transfers are set to zero is that the loss of a transfer would not be compensated for by other kinds of transfers. However, in reality this is often not the case; the absence of a transfer might lead not only to changes in taxes and SIC, but also to variations in other means-tested benefits. This is exactly the case in scenario 3, in which public old age and survivors' pensions are set to zero, and scenario 4, in which non-means-tested benefits are eliminated. Table 7.3 presents the effects of these two scenarios on the AROP rate. The comparison between AROP_3 (AROP_4) and AROP_0 provides the contribution of gross public pensions (non-means-tested benefits) to income poverty reduction. The comparison between AROP_3p (AROP_4p) and AROP_0 provides the contribution of net public pensions (non-means-tested benefits) to poverty reduction, accounting for all complex policy interactions.

On average across the EU-27 countries, gross public pensions reduce the AROP rate by 18.6 p.p. whereas net public pensions combined with increased means-tested benefits by 16.4 p.p. As Table 7.3 and Figure 7.5 show, the difference between AROP_3 and AROP_3p exceeds 5 p.p. in four EU countries (Austria, Portugal, the Netherlands and Poland) and is statistically significant and greater than 1 p.p. in another 15 countries.

We shall now investigate whether this difference is due to reduced taxes/SIC paid by individuals when pensions are considered in net terms or it is due to the increases in means-tested benefits that replace part of the pension losses. Our estimates, presented in Figure 7.5, suggest that in Austria, Portugal and the Netherlands it is mostly the latter; the increase in social assistance benefits explains 71 %, 85 % and 67 %, respectively, of the total difference in the AROP rates. The same holds for Slovakia, Hungary, Cyprus and Romania, where policy interdependencies explain from 70 to 100 % of the total difference. On the other hand, the countries where most of the difference is explained by reduced taxes/SIC are Luxembourg, Denmark, Sweden, Italy, France, Greece, Belgium, Germany, Spain, the United Kingdom and Latvia. In total, net public pensions per se (i.e. when the impact of policy interactions is removed) reduce the AROP rate by 17.3 p.p. The difference between the gross and net AROP rates before pensions (the orange bar in Figure 7.5) never exceeds 3 p.p.

Another at first glance counter-intuitive result is that, in Greece, the difference between AROP_1 and AROP_1p (1.1 p.p.) is smaller than the difference between AROP_3 and AROP_3p (1.8 p.p.). This highlights the importance of the position of individuals affected by the lack of pensions and/or benefits in the income distribution. The reduction of taxes/SIC paid in scenario 1, in which all public pensions and benefits are set to zero, lifts fewer individuals above the (fixed) poverty threshold than it does in scenario 3, in which benefits are still present and only public pensions are not accounted for.

Moving to non-means-tested benefits, their anti-poverty impact in both gross and net terms seems to explain most of the total impact of all benefits (both means-tested and non-means-tested) on income poverty reduction. Gross non-means-tested benefits reduce the AROP rate by 7.4 p.p. on average across the EU-27, and net non-means-tested benefits, together with policy interactions, by 6.1 p.p., although the impact of all benefits reaches 9.9 p.p. In Austria, income poverty is lower when non-means-tested benefits are deducted in gross terms than in net terms, as shown by the negative bar in Figure 7.6. This is because, when non-means-tested benefits are set to zero, some individuals end up paying more personal income tax, as they lose access to child tax credits (the non-means-tested family allowance acts as a passport to this credit). As can be seen in Figure 7.6, the total difference between AROP_4 and AROP_4p exceeds 2 p.p. in seven EU countries (the Nordic countries along with the Netherlands, Slovenia, Germany and Belgium). In Finland, the Netherlands and Germany this difference is mostly driven by increases in means-tested social assistance benefits due to the loss of non-means-tested benefits. Net non-means-tested benefits alone (i.e. without accounting for policy interactions) reduce the AROP rate by 6.7 p.p.; this is very similar to the reduction achieved if benefits are considered in gross terms. Only in the three

Nordic countries does the difference in the AROP rates between gross and net non-means-tested benefits alone reach 2 p.p. or more.

The ranking of countries in terms of the anti-poverty effectiveness of their public pensions and non-means-tested benefits in net and gross terms, and allowing for policy interactions, is depicted in Figures 7.7 and 7.8. The country where pensions achieve the highest poverty reduction in both gross and net terms is Greece. A substantial amount of re-ranking takes place. For example, Poland, where gross pensions achieve the second-best poverty reduction, falls to 8th place if pensions (combined with policy interactions) are considered in net terms, and Austria falls from 4th to 15th. When countries are ranked according to the anti-poverty effectiveness of gross and net non-means-tested benefits, most of the repositioning takes place in the middle and lower parts of the ranking. These findings suggest that even small changes in the assumptions used to construct the relevant EU indicators might have an important impact on the estimated effectiveness of social transfers on income poverty.

Finally, the examination of the anti-poverty impact of gross and net means-tested benefits (scenario 5, Table 7.3) shows that, on average among the EU-27, gross means-tested benefits reduce the AROP rate by just 3.9 p.p. and net means-tested benefits reduce it by 3.8 p.p. The difference between AROP_5 and AROP_5p is equal (or very close) to zero in 27 out of the 28 countries. The only exception is Finland, where the difference reaches 1 p.p. The countries where means-tested benefits achieve the biggest poverty reduction (in both gross and net terms) are, by far, the United Kingdom and Ireland. The ranking of countries barely changes when these benefits are considered in net or gross terms.

Table 7.3: **AROP rates, baseline and deducting public pensions, non-means-tested and means-tested benefits in gross and net terms, EU-27 and United Kingdom, 2015**
(%)

Countries	AROP_0	AROP_3	AROP_3p	AROP_4	AROP_4p	AROP_5	AROP_5p
Belgium	11.1	30.9	29.6	20.8	18.7	16.8	16.8
Bulgaria	22.3	36	35.8	25.9	25.7	24.7	24.7
Czechia	9.1	30.1	29.8	15.2	14.3	11.7	11.7
Denmark	10.3	26.2	23.1	23.6	18.1	16.1	15.9
Germany	15.4	35.1	33.8	21.4	19.3	18.8	18.8
Estonia	21.2	33.1	32.9	29.1	28.3	21.2	21.2
Ireland	14.1	27.6	27.2	23.2	22.3	26.1	26
Greece	19.6	48.8	47.1	21.5	21.4	23.8	23.8
Spain	22.2	40.9	39.7	28	27.4	24.6	24.6
France	12	34.3	31.9	18.5	17	18.7	18.7
Croatia	19.5	34.8	34.5	27.4	26.7	22.4	22.4
Italy	18.2	40.8	38	24.8	23.6	20.6	20.6
Cyprus	14.9	28.1	26.7	21.3	20.8	22	22
Latvia	22	36.2	35.1	27.3	27.2	22	22
Lithuania	21.5	36.5	36.1	28	27.6	23.4	23.4
Luxembourg	9.7	30.8	27	24.6	22.9	14.4	14.4
Hungary	18.9	42.4	40.9	27	26.4	20	20
Malta	15.2	30.7	30.3	20.3	20.2	21.8	21.8
Netherlands	11.2	24.5	18.2	19.4	16.4	19.2	19.1
Austria	12.1	34.8	27.8	21.9	23.1	16.8	16.7
Poland	17.6	41.3	36.1	22.3	20.8	19.4	19.4

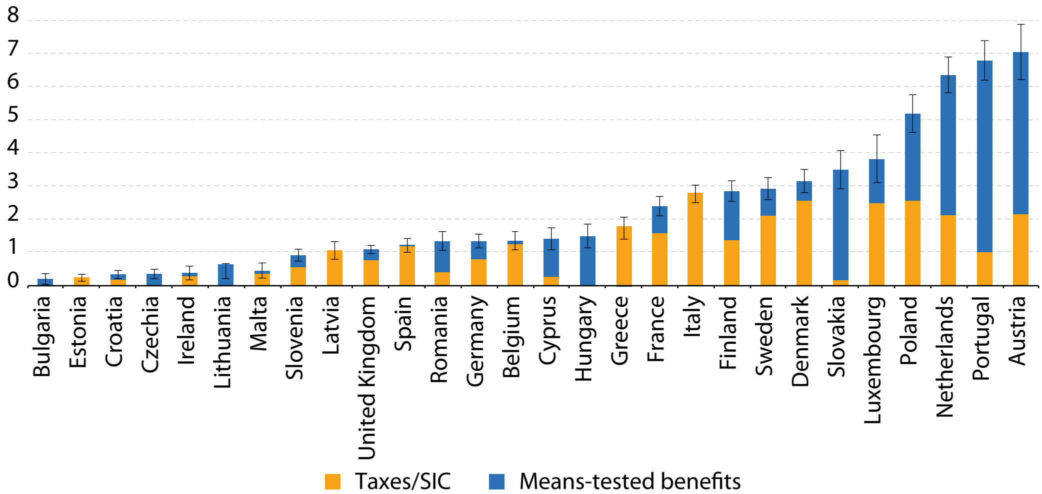
Countries	AROP_0	AROP_3	AROP_3p	AROP_4	AROP_4p	AROP_5	AROP_5p
Portugal	19.1	41.1	34.3	24.4	24.2	21.4	21.4
Romania	23.8	44.5	43.2	28	27.6	26.2	26.2
Slovenia	14.4	32.7	31.8	23.3	20.8	18	17.8
Slovakia	11.4	30.9	27.4	17	16.8	12.8	12.9
Finland	10.5	30.4	27.5	22.3	17.6	18.6	17.7
Sweden	14.6	30.8	27.9	24.9	22.6	15.9	15.9
United Kingdom	15	25.3	24.3	22.1	21.5	28.5	28.5

Reading note: In Romania, the baseline AROP rate is estimated to be 23.8 %, and the AROP rate before all gross public old age and survivors' pensions in gross terms is 44.5 %. The comparison with the baseline AROP (AROP_3 – AROP_0) provides the contribution of all gross public old age and survivors' pensions to poverty reduction. In net terms, the AROP rate before public old age and survivors' pensions is estimated to be 43.2 %.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.5: Disentangling the anti-poverty effects of pensions, EU-27 and United Kingdom, 2015

(p.p.)

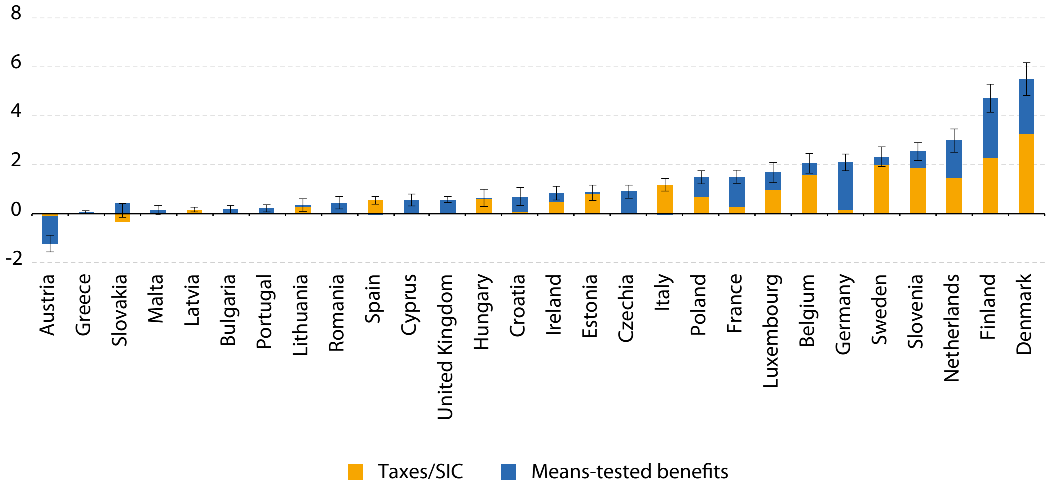


Note: Countries are ordered according to the difference between AROP_3 and AROP_3p. Standard errors for 95 % confidence intervals are calculated using DASP.

Reading note: In Portugal, the difference between the contribution of all gross social pensions to poverty reduction and the contribution of all net pensions (accounting for policy interactions) to poverty reduction is 6.8 p.p.; policy interactions explain 85 % of this difference.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.6: Disentangling the anti-poverty effects of non-means-tested benefits, EU-27 and United Kingdom, 2015
(p.p.)

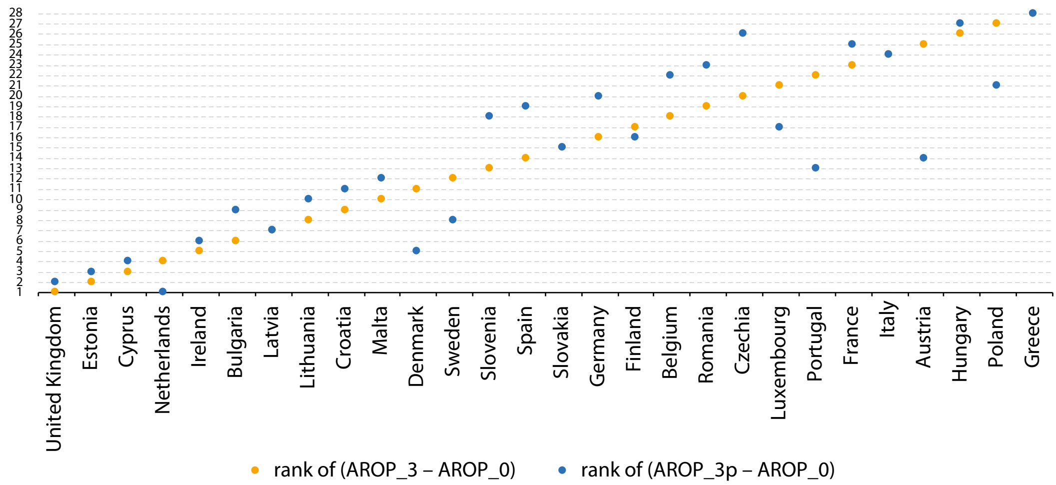


Note: Countries are ordered according to the difference between AROP_4 and AROP_4p. Standard errors for 95 % confidence intervals are calculated using DASP.

Reading note: In Germany, the difference between the contribution of all gross non-means-tested benefits to poverty reduction and the contribution of all net non-mean-tested benefits (accounting for policy interactions) to poverty reduction is 2.1 p.p.; policy interactions explain 92 % of this difference.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.7: Country ranking by contribution of gross and net public pensions to income poverty reduction, EU-27 and United Kingdom, 2015

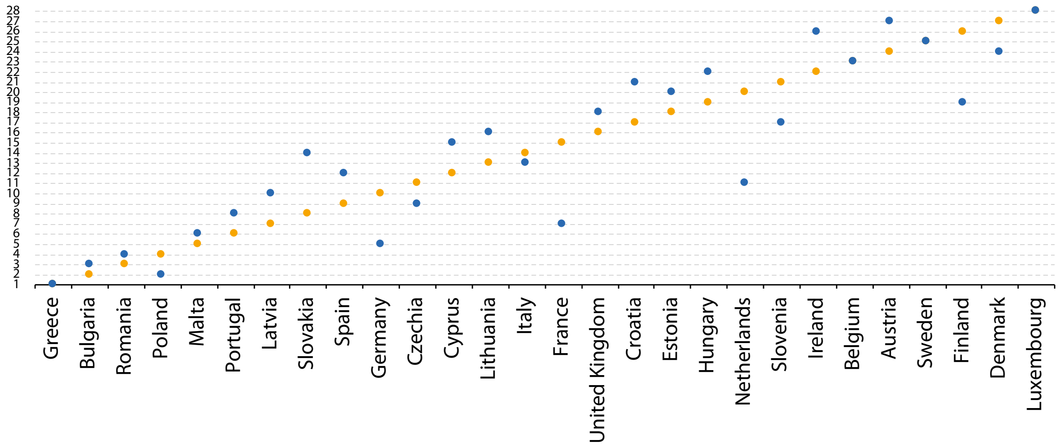


Note: Countries are ordered according to the rank of (AROP_3 – AROP_0).

Reading note: Poland occupies 2nd place in terms of income poverty reduction achieved by gross pensions; it falls to 8th place if pensions (combined with policy interactions) are considered in net terms.

Source: Authors' calculations using EUROMOD Version H1.0.

Figure 7.8: Country ranking by contribution of gross and net non-means-tested benefits to income poverty reduction, EU-27 and United Kingdom, 2015



Note: Countries are ordered according to the rank of (AROP_4 – AROP_0).

Reading note: Finland occupies 3rd place in terms of income poverty reduction achieved by gross non-means-tested benefits; it falls to 10th place if non-means-tested benefits (combined with policy interactions) are considered in net terms.

Source: Authors' calculations using EUROMOD Version H1.0.

7.4. Conclusion

The aim of this research has been to measure the effects of social transfers on the reduction of income poverty by exploring alternative ways of defining transfers to the way these are taken into account in the current relevant EU indicators. Although these EU indicators should ideally use the concept of disposable income before net social transfers (by deducting from disposable income the amount of net social transfers), they are constructed by deducting gross transfers. Furthermore, the EU indicators simply deduct the amount of gross transfers from disposable income without accounting for interdependencies between social transfers. Finally, the EU indicator does not distinguish the anti-poverty effect of means-tested and non-means-tested benefits. In this chapter, we set out to analyse the effects of treating social transfers in net or gross terms, the roles of pensions, means-tested benefits and non-means-tested benefits, and the impact of policy interdependencies when constructing hypothetical scenarios in which some transfers are set to zero. The policy year considered for all EU Member States and the United Kingdom was 2015. The microsimulation model EUROMOD, with input data based on EU-SILC 2015, was used to construct a baseline and six hypothetical scenarios. The research of Goedemé and Zardo Trindade (2020) has shown that the computation of taxes and SIC paid on social transfers for the purposes of constructing the relevant net and gross variables in EU-SILC varies widely among European NSIs. The use of EUROMOD allows us to define transfers in net terms in a transparent and comparable way.

A certain amount of caution is called for when interpreting our results. The main issues, to do either with our approach or with our assumptions, are briefly discussed below. First, accounting for tax evasion is limited to the models of Bulgaria, Greece and Italy. In Bulgaria, tax evasion adjustments are based on a comparison between net and gross employment incomes. In Greece, these adjustments have been made on the basis of external estimates for the extent of average income under-reporting by income source (earnings, farming income and non-farm business income). In Italy, self-employment income has been calibrated to account for tax evasion. Second, because of data limitations, accounting for benefit non-take-up has only been possible in the models of Estonia, Greece, France, Croatia, Portugal and Romania. Clearly, a more uniform treatment of these issues would enhance the precision of our findings. Finally, even though a microsimulation approach allows us to simulate the tax–benefit systems of countries with a high degree of accuracy, certain aspects of the systems may still be simplified or not simulated at all.

The most important results can be summarised as follows. First, we find that the treatment of taxes and SIC has an important impact on the indicators used to assess the anti-poverty impact of social transfers. The average contribution of net transfers to poverty reduction (scenario 1) in the 28 countries under consideration is 1.5 p.p. smaller than the corresponding contribution of gross transfers. The countries where the poverty-reducing effect of transfers is most significantly overestimated if these are considered in gross terms are Denmark, Finland, Sweden, the Netherlands, Italy and Luxembourg. Interestingly, in Slovakia and Lithuania income poverty is slightly lower when transfers are deducted in gross terms, as some benefit recipients who were previously SIC-exempt end up paying more health insurance contributions. In the scenario in which only benefits (not pensions) are set to zero (scenario 2) the poverty-reducing effect of these benefits is overestimated by 0.6 p.p. on average if these are considered in gross terms. At national level, this overestimation is also generally small, with the only exceptions being the Nordic Member States, where this difference varies from 2 to 2.8 p.p.

In scenarios 3 and 4, the (simulated) absence of public pensions or non-means-tested benefits leads not only to changes in taxes and SIC, but also to variations in other means-tested benefits, as pensioners may become eligible for means-tested benefits when their pensions are set to zero. Our results suggest that gross public pensions reduce the AROP rate by 18.3 p.p. on average, whereas net public pensions combined with increased means-tested benefits reduce it by 16.1 p.p. Subtracting net public pensions from disposable income without taking into account the impact of interactions between transfers reduces the AROP rate by 17.3 p.p. The anti-poverty impact of non-means-tested benefits seems to explain most of the total impact of all benefits on income poverty reduction; gross non-means-tested benefits reduce the AROP rate by 7.4 p.p. on average, and net non-means-tested benefits combined with policy interactions (per se) reduce it by 6.2 (6.7) p.p. This finding is consistent with Nelson (2004, p. 386), whose analysis also shows that when it comes to alleviating poverty 'more may be gained from an extension of existing non-means-tested entitlements, in particular in the area of social insurance'.

Our analysis has shown that measuring the effects of social transfers on the reduction of income poverty in net or gross terms does matter. The main reason is that, depending on the choice made, the ranking of countries in terms of the anti-poverty effectiveness of their monetary social provision systems changes – sometimes quite dramatically. Hence, even small discrepancies in the assumptions used by national statistical offices to construct the relevant EU indicators might have an important impact on the estimated country rankings, which are frequently used for policy recommendations.

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8 By how much do social transfers reduce material deprivation in Europe?

Geranda Notten and Anne-Catherine Guio (118)

8.1. Introduction

As explained in Chapter 1, the EU adopted in 2010 a social inclusion target of lifting at least 20 million people from poverty and social exclusion by 2020. At the end of the decade, we have to recognise that the EU has not made the expected progress towards achieving its social inclusion target – which is still more than 11 million higher than the initial 96 million-target. It is therefore important to remain vigilant in assessing the role and effectiveness of the policies adopted to combat income poverty and social exclusion in Europe. Making methodological improvements is also necessary, especially in areas where the existing toolbox lacks tools to assess the effect of policies on a stated policy goal.

The Europe 2020 social inclusion target recognises the importance of three dimensions of poverty and social exclusion: financial poverty, SMD and joblessness (see Chapter 1 of the present volume). The level and distribution of social transfers in each country are particularly influential factors in reducing income poverty and material deprivation. Although long-established methodologies for evaluating the effect of social transfers on disposable income exist at EU level (see Chapter 6 of the present volume), this is not the case for material deprivation.

This chapter summarises the main findings of Notten and Guio (2020), who developed an approach to estimating the effect of an increase in transfers on the new MSD indicator (see Guio et al., 2017, and Chapter 1 above). It shows that the impact on deprivation of a universal annual EUR 150 social transfer (expressed in PPS) is higher among persons who have fewer resources, an effect that is present both within and across countries and underlines the importance of a progressive social transfer system. A small universal 150 PPS transfer per year would reduce the number of Europeans with five or more deprivations by 876 000.

Building on previous research (Notten, 2015; Notten and Guio, 2016), this approach has broader applicability, suiting social indicators whose scaling has similar properties, such as housing deprivation indicators.

Section 8.2 describes the methodology and the data. Section 8.3 applies the methodology by analysing the predicted impact of a universal transfer on MSD. Section 8.4 concludes.

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8.2. Method, data and model specification

8.2.1. Method

The typical operationalisation of material deprivation implies that a person is only considered deprived when they cannot achieve a particular 'doing' or 'being' because they do not have the financial resources (Guio et al., 2017; Guio, 2009; Saunders and Wong, 2011).

Material deprivation focuses on a person's ability to finance the doings and beings that are customary, or at least widely encouraged or approved, in the society the person lives in (Townsend, 1979; Sen, 1999). By providing social transfers, the state supplements the market income (net of taxes) of people, who thereby have more resources to finance the things they want to do and be (Barr, 2012; Sen, 1999). Social transfers can thereby reduce material deprivation for people who would otherwise not have enough financial resources to finance their doings and beings. For some people, social transfers have no effect on material deprivation because they have sufficient resources to meet these customary doings and beings without receiving transfers.

To estimate the impact of social transfers on material deprivation, this chapter uses a regression-based empirical strategy. It estimates the impact of income, of which social transfers are one source, on the new MSD indicator. Then it uses the regression model to predict the effect of a marginal additional transfer on the deprivation rate. Thus, the impact of a small additional transfer on MSD is measured as the difference between the predicted number of deprivations estimated using the total disposable household income (as collected in the survey) and the predicted number of deprivations estimated using the household income increased by a small amount of transfers.

A marginal impact analysis is less likely to violate the strong assumptions required for such an analysis. For instance, the analysis assumes that transfer recipients make the same choices (with respect to work, care and spending) with or without the additional transfer, that is, that the social transfers does not lead to behavioural changes. This assumption may be plausible for small transfers (relative to a person's other resources) but increasingly difficult to defend as transfers become more substantial. The methodology further assumes that the transfer amount is the only aspect that affects a person's access to publicly provided resources. The reality is that countries' social protection systems are complex, comprising both cash and in-kind benefits, with some benefits acting as complements and others as substitutes. Thus, a change in a social transfer received from one cash transfer programme may trigger additional benefits (underestimating the effect of the treatment), whereas one received through another programme reduces benefits received from other programmes (overestimating the effect of the treatment). In Section 8.2.3, we go on to discuss how challenges in the EU-SILC data result in unobserved heterogeneity between observations from the same country, which in turn can bias the estimated impacts in unknown ways.

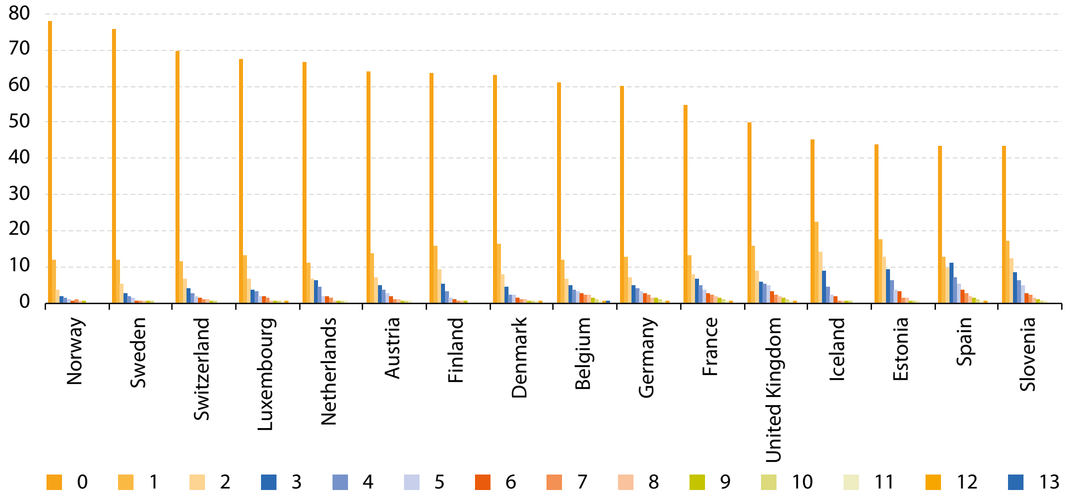
The impact of the additional transfer is assessed for each country separately, by estimating our preferred model at country level. The EU-SILC countries are indeed very heterogeneous in terms of living standards, economy, labour market, welfare state, demography and culture. It is therefore reasonable to expect variation in parameter values between countries (in terms of magnitude but possibly also the significance and sign of some control variables).

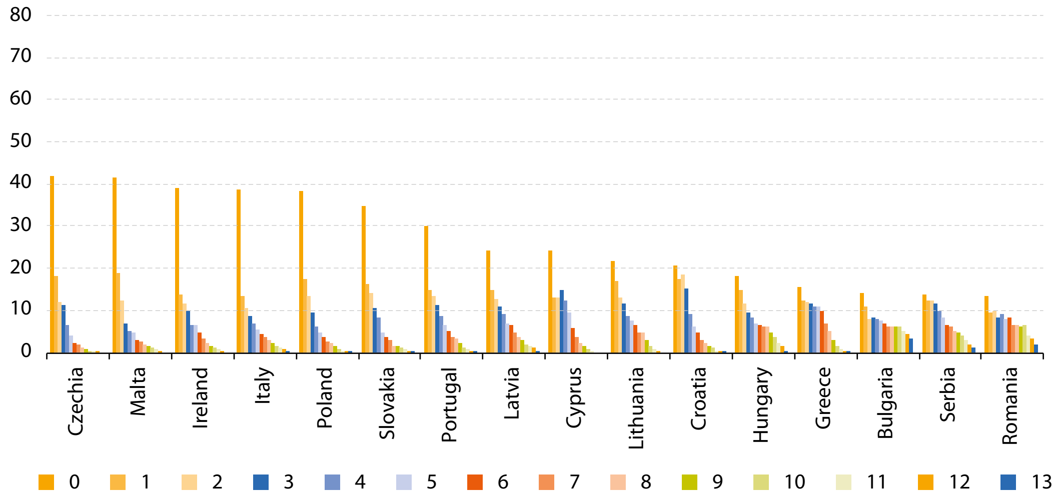
8.2.2. Dependent variable

The dependent variable reflects the number of material and social deprivations suffered by each individual (see definition in Chapter 1). Whereas the EU's new MSD indicator is a binary variable reflecting the percentage of people not able to afford five or more items, we use the entire deprivation scale as our dependent variable to avoid losing potentially valuable information.

The number of missing values for the MSD count is limited in most countries, except in Ireland, Switzerland and the United Kingdom (where it reaches 23 %, 12 % and 11 % respectively for at least one item). These countries are included in the analysis for illustrative purposes, but we cannot exclude the possibility that the missing information is selective and that this has an effect on the sample representativeness.

Figure 8.1: Dependent variable – the number of item deprivations (0–13), 2015
(% of individuals)





Note: Ranked according to highest percentage of zero deprivations.
Reading note: In Belgium, the percentage of people not suffering from any deprivation (out of 13) is around 60 %.
Source: Authors' computations, UDB September 2017.

Figure 8.1 displays the distribution of the number of deprivations for each country, ordered from a high to a low population share with zero deprivations to facilitate analysis of the variation of the distribution by average living standard. The percentage of individuals with zero deprivations is the largest group in each country. In most countries, the distribution decreases monotonically, but there are some exceptions (Spain, Cyprus, Croatia and Romania). As the average living standard decreases, the percentage of individuals with one or more deprivations increases.

8.2.3. Independent variables

Despite the fact that the relation between income and deprivation is far from perfect (Fusco et al., 2010), income remains the most influential determinant of deprivation. In addition to income, a person's characteristics (personal) and those of their environment (family, community, state, society) play a key role in the person's capacity to transform the resources they command to avoid material deprivation. These characteristics include (non-income) resources and other factors influencing one's needs and costs (see also Chapter 13 for a similar discussion about the determinants of child deprivation).

Social transfers are part of a household's income and thereby contribute to the level of financial resources that persons have to meet their social and material needs. We define the impact of a small additional transfer on MSD as the difference between the predicted number of deprivations estimated using the EU-SILC total disposable household income and the predicted number of deprivations estimated using the total disposable household increased by a small amount of transfers. The independent variable used is the equivalised disposable household income variable (HY020 divided by HX050) adjusted for cross-national differences in PPS. Given the large differences in scale between this and the other explanatory variables, we further rescale income into thousands of euro.

As some of the necessary information is available only for adults or at household level, we have to assume that persons living together in a household pool resources and take account of members' needs in employing them. Some of the variables are not available in the data (n.a.), of insufficient quality (IQ) or excluded for reasons such as multicollinearity, lack of explanatory power, parsimony and consistency in model specification across different estimators (EX):

- resources or lack thereof:
  - adjustments to disposable income:
    - imputed rent (IQ) ([119]);
    - monetary value of home production of goods for own consumption (IQ) ([120]);
  - (in)adequacy of financial resources:
    - dummies indicating if housing costs are a financial burden (heavy and slight);
    - dummies indicating if debt payment is a financial burden (heavy and slight);
  - proxies for wealth:
    - income from property and capital (IQ);
    - housing tenure status (owner, paying mortgage, paying rent);
    - taxes on wealth (IQ);
  - access to public goods and services, including in-kind transfers (n.a.) ([121]);
  - availability and affordability of childcare / after-school care (EX);
  - access to other resources such as social capital (n.a.);
  - interaction between income, other resources and/or conversion factors (i.e. proxies for wealth, burden of debt and housing costs, self-perceived health and limitation in activities) (EX);
- other factors:
  - dummy for low self-perceived health of adult members and/or limitation in activities because of health problems of adult members;

([119]) On the quality of imputed rent variable and its impact on the income distribution, see Törmalehto and Sauli (2017).
([120]) For a study on the quality of self-consumption income in EU-SILC, see Čomić (2021).
([121]) On the distributional impact of public services on income, see Aaberge, Langørgen and Lindgren (2017).

- dummy for chronic illness of adult members (EX);
- dummy for a household with dependent children;
- the number of dependent children in the household;
- the number of adults in the household;
- dummies for education level of member with highest education (primary, secondary, tertiary);
- dummy for non-EU country of birth of adult members;
- dummy for low work intensity household ([122])
- dummies for self-reported economic status of adult members (unemployment and retired);
- dummies for region, where available.

Although EU-SILC is the best data available for cross-national comparisons in Europe, the above list indicates that data challenges remain. Of particular concern is the absence of information on a person's access to non-income resources. All other things being equal, a person with access to alternative resources is likely to have a lower deprivation level than a person with the same income but with meagre access to alternative resources. There is thus unobserved heterogeneity between observations from the same country, the effects of which bias the income and other regression parameters to an unknown extent. Moreover, systematic differences in the composition of resources between countries (e.g. the prevalence of home production for own consumption or the relative importance of in-kind versus cash public transfers) also biases the cross-national comparison of impact estimates presented in Section 8.3 to an unknown extent. For country-specific research, alternative national-level microdata may offer a partial remedy to this missing data problem. For our research, however, this option is not available.

([122]) The household work intensity is the ratio of the total number of months that all working-age (18–59) household members have worked to the total number of months the same household members could have worked in theory.

8.2.4. Regression estimators and model specification

The theory underlying the measurement of Europe's material deprivation indicator offers some guidance on which regression estimators may be appropriate to estimate the relation between material deprivation and income. According to Guio, Gordon and Marlier (2012), material deprivation reflects an individual trait that researchers cannot directly observe, but that they measure indirectly by collecting information about a person's capacity to afford (a limited set of) consumer durables and social activities. Material deprivation is thus a latent variable and, together, the deprivation items form the scale on which this concept is measured. Using the material deprivation scale, one should be able to distinguish between non-deprived and deprived persons (discrimination). Moreover, for deprived persons, the scale makes it possible to distinguish between various degrees of deprivation (severity). The scale reflects the number of items that a person cannot afford, taking on integer values between 0 and 13. As Figure 8.1 shows, the variable has an asymmetric distribution, with the highest density at zero and densities for subsequent values gradually tapering off.

Given such properties, suitable regression models treat the dependent variable as either a count variable or an ordered variable (Long and Freese, 2014). In a count regression, the underlying model assumes that a one-unit change in deprivation level reflects the same substantive change at every possible level. Thus, an improvement from five to four deprivations should reflect, on average, the same substantive improvement as that from one deprivation to zero. An ordered regression requires a weaker assumption, requiring only that lower values of the dependent variable reflect lower deprivation levels.

Notten and Guio (2020) tested the empirical performance of three count models, namely the Poisson model, the negative binomial model and the zero-inflated negative binomial model.

- The Poisson model assumes that the mean is equal to the variance. In practice, the Poisson rarely fits because of overdispersion (Long and Freese, 2014, p. 507).

- The negative binomial model addresses overdispersion by adding a parameter (α) that reflects unobserved heterogeneity among observations (Long and Freese, 2014, p. 507).
- The zero-inflated model is a two-step estimator. As the number of zero values is often larger than expected by a Poisson or negative binominal distribution, this model assumes two data-generating processes, the first step estimating a binary model to identify the group of people who have structurally no deprivation, followed by estimating a usual count model (typically a Poisson or a negative binominal model) to estimate the number of items lacked ([123]).

The authors showed that the zero-inflated models outperform the Poisson model and the negative binomial model in most countries. They argue that the assumption underlying zero-inflated models captures well the nature of the deprivation data. Indeed, by design, the material deprivation variable only measures the lower part of the material well-being distribution (i.e. it does not measure a person's financial capacity to purchase high-end sports cars or a second house). A person who has enough financial resources to afford the 13 customary items has a value of zero deprivations, irrespective of whether that person has just enough or ample resources. Thus, the variation in resources within this group of observed zeros is likely to be larger than that observed for another deprivation value. Moreover, this within-group variation tends to increase as the average living standard of a country rises, because that usually also means a rise in the population share of the zero value group (as illustrated in Figure 8.1). From the above argument, people having zero deprivation probably consist of two separate groups. Zero-inflated models assume precisely that zero values can have two different origins: structural and sampling. In the case of deprivation, the group of people who have so many resources that their chances of material deprivation are indistinguishable from zero can be considered structural zeros. The other group, people who are currently able to get by but may be one or two adverse events removed from experiencing deprivation, can be considered sampling zeros.

Notten and Guio (2020) also compared the performance of the count models with that of ordered models. The ordered models are less restrictive than count models because they treat the different deprivation values as ranked categories instead of equidistant categories. They argue that, given the construction methodology of deprivation indicators, there is a priori no reason to expect that the substantive distance between deprivation categories would be constant over the entire deprivation distribution. Previous research showed that there is an order of deprivation (Guio and Pomati, 2017). Usually, people lacking only one item suffer from one of the least severe problems (lack of holidays, shortage of furniture or incapacity to face unexpected expenses). Those lacking more items combine less severe and more severe items. As the severity differs between items (see Guio et al., 2017), we may expect that the steps of the deprivation scale are not equidistant either. Notten and Guio (2020) therefore tested the two following ordered regression models.

- The ordered logistic model is a model that absorbs variation in levels of deprivation in different constants (also called thresholds, as they represent differences between consecutive values of the latent variable). This model assumes that the coefficients of the explanatory variables have the same value across deprivation levels. This means that a given change in income (or another explanatory variable) has the same effect at different deprivation levels (parallel slope assumption).
- The generalised ordered logit model relaxes this assumption and allows the coefficient of one or more explanatory variables to differ between deprivation levels. This could be relevant, as a given change in income (or another explanatory variable) may not have the same effect at different deprivation levels.

Based on previous results (Notten, 2015; Notten and Guio, 2016), Notten and Guio (2020) maximised the model fit by using as far as possible the variables available in EU-SILC (Section 8.2.3) to apprehend the diversity of risk factors in each EU-SILC country and the complex interrelations between explanatory variables.

([123]) Although Beduk (2018) also recognised the importance of treating people suffering from no deprivation (zeros) separately, he opted for a hurdle model, which does not, in our view, take account of the heterogeneity of zeros.

In reproducing the observed MSD distribution, Notten and Guio's different tests unambiguously showed that (generalised) ordered regression models perform better than count models. They showed that the generalised ordered logit model marginally outperforms the ordered logit model, but not in all countries and not for the highest deprivation levels. Even though in many countries (but for differing variables) flexibility in the coefficients across levels of deprivation, as possible only in the generalised ordered logit model, would be desirable, they argue that the cost of increased complexity is not worthwhile in the context of the country comparison of all EU-SILC countries. They therefore suggest use of the ordered regression model. They also show that the calculated impacts of a transfer on MSD are very similar for both ordered models.

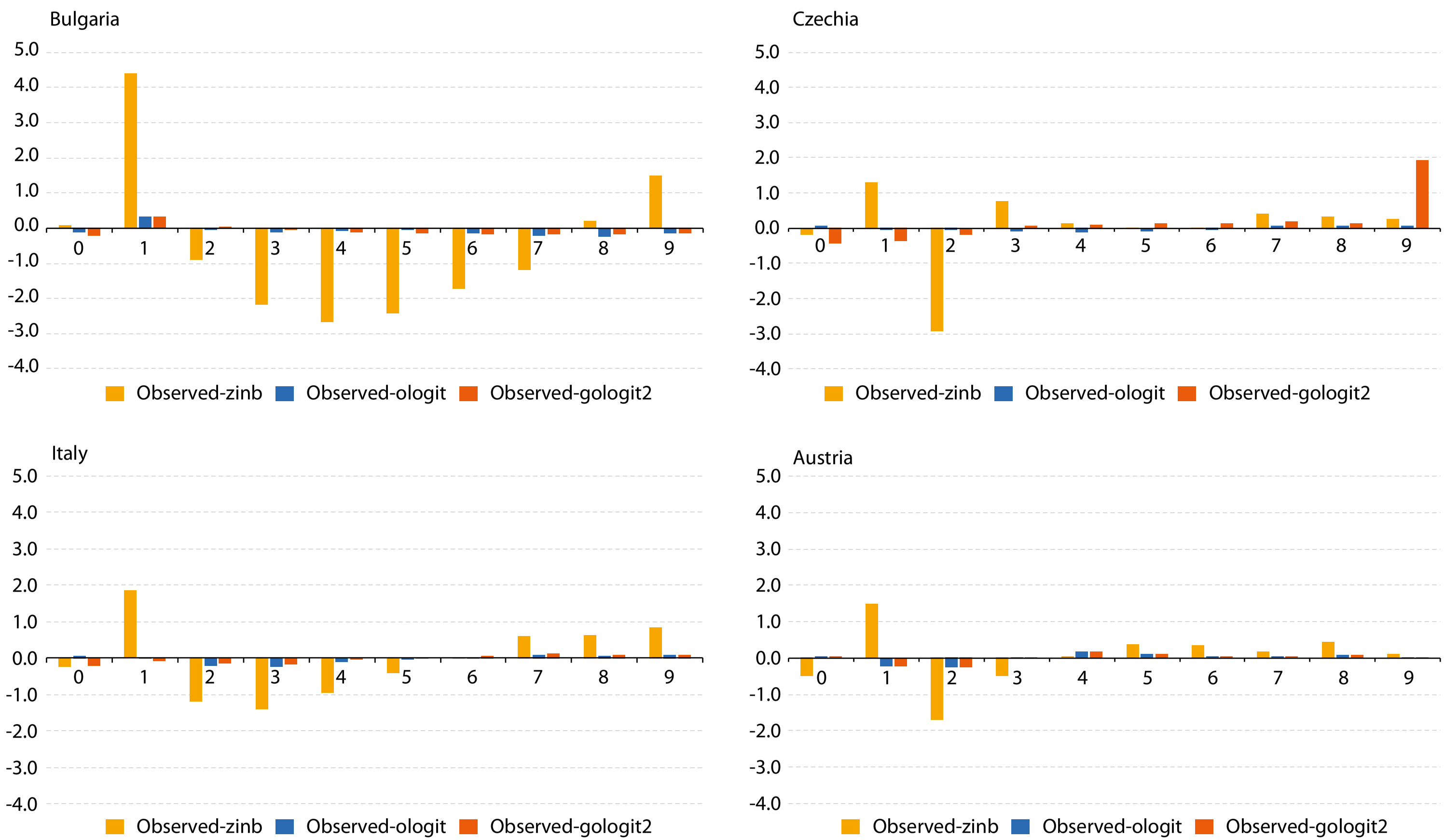
To illustrate the fit of different models, Figure 8.2 compares, for a selection of countries, the p.p. deviation between the predicted and the observed population shares (y-axis) at different values of the deprivation count distribution (x-axis) for the best three estimators: the zero-inflated negative binomial model, the ordered logistic model and the generalised ordered logistic model. If a deviation at a given count value is positive, the model underpredicts the number of observations relative to the number actually observed (and vice versa for negative values). Whereas deviations of 1 p.p. and higher are common for the zero-inflated model, those deviations are typically below 0.02 p.p. for the two ordered logistic models for most deprivation values in most countries.

Table 8.1 presents the results of the ordered regression for a selection of countries ([124]). Please note that this model includes 13 cut-off points, which indicate the different thresholds of the latent variable (MSD) identifying the 14 deprivation values observed in our data. Note also that this model assumes that the latent variable is continuous, which is what the theoretical framework assumes. These regression results are in line with the literature on material deprivation (see also Chapter 13 of the present volume). The income coefficient is negative and statistically significant from zero in all countries. Similarly, the coefficients of variables associated with lower resources are positive and statistically significant in all countries (i.e. debt and housing costs being a financial burden or being a tenant). Variables related to barriers / additional costs, such as low household work intensity, presence of unemployed members, low education level and health problems, have the expected significant positive impact. For other variables, the signs of the coefficients differ between countries and/or are statistically significant from zero in some but not in other countries. Such cross-national differences also occur for the demographic variables, reflecting differences in the societal structures among European countries.

Despite our efforts to use the available information as far as possible to improve the prediction of MSD using EU-SILC data, Figure 8.2 illustrates the difficulties in satisfactorily predicting the distribution of deprivation values, particularly in the poorest countries. In Bulgaria, for example, the ordered logistic models underestimate population shares with one deprivation while overestimating those with higher or no deprivation. This suggests there might be scope for improving the model specification, particularly at country level, or performing a smaller cross-national comparison of more similar countries.

([124]) In addition to sample restrictions mentioned earlier, the estimation presented in Table 8.1 excludes a small number of observations for which the ordered logit model is completely determined. Following Stata's automatically generated error message and the diagnostic steps suggested on Stata's user forum (accessed 15 January 2019), we find that in all countries these are observations whose predicted probability of zero deprivations is either 1 or very close to 1. Following this finding, we apply the recommended solution of dropping these observations from the model's estimation (while including them using the model for predictions). These regression results are obtained without top-coding the dependent variable above nine deprivations, whereas, for ease of programming, all other results in this section are obtained using the top-coded variable.

Figure 8.2: Goodness of fit: deviation between observed and predicted distribution by estimator, 2015
(p.p.)



Note: P.p. deviation between observed and predicted distribution: zero-inflated negative binomial (zinb), ordered logistic (ologit), and generalised ordered logistic (gologit2). Prediction based on sample used to estimate the model. Distribution displayed up to nine deprivations; numbers rounded to a single digit.

Reading note: A positive value indicates underprediction of the share of people lacking X items, compared with the observed share.

Source: Authors' computations, UDB September 2017.

Table 8.1: Results of the ordered logistic model (preferred model), 2015

<table>
<tr><th>Variable of interest</th><th>Austria</th><th>Czechia</th><th>Italy</th><th>Bulgaria</th></tr>
<tr><td>Income (in 1 000 PPS)</td><td>-0.067***</td><td>-0.186***</td><td>-0.069***</td><td>-0.190***</td></tr>
<tr><td>Thresholds</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Cut1</td><td>0.671**</td><td>-0.563*</td><td>0.334</td><td>-1.973***</td></tr>
<tr><td>Cut2</td><td>1.693***</td><td>0.539*</td><td>1.199***</td><td>-0.994***</td></tr>
<tr><td>Cut3</td><td>2.401***</td><td>1.341***</td><td>1.895***</td><td>-0.431</td></tr>
<tr><td>Cut4</td><td>3.066***</td><td>2.309***</td><td>2.512***</td><td>0.062</td></tr>
<tr><td>Cut5</td><td>3.660***</td><td>3.145***</td><td>3.058***</td><td>0.493</td></tr>
<tr><td>Cut6</td><td>4.255***</td><td>3.869***</td><td>3.560***</td><td>0.886**</td></tr>
<tr><td>Cut7</td><td>4.846***</td><td>4.504***</td><td>4.029***</td><td>1.260***</td></tr>
<tr><td>Cut8</td><td>5.373***</td><td>5.213***</td><td>4.521***</td><td>1.610***</td></tr>
<tr><td>Cut9</td><td>6.158***</td><td>5.933***</td><td>5.026***</td><td>1.995***</td></tr>
<tr><td>Cut10</td><td>6.925***</td><td>6.759***</td><td>5.632***</td><td>2.440***</td></tr>
<tr><td>Cut11</td><td>8.272***</td><td>7.640***</td><td>6.209***</td><td>2.969***</td></tr>
<tr><td>Cut12</td><td>9.097***</td><td>8.363***</td><td>7.085***</td><td>3.630***</td></tr>
<tr><td>Cut13</td><td>9.851***</td><td>9.563***</td><td>8.657***</td><td>4.609***</td></tr>
<tr><td>Other explanatory variables</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Health problem</td><td>0.580***</td><td>0.454***</td><td>0.443***</td><td>0.311***</td></tr>
<tr><td>Debt is a heavy burden</td><td rowspan="2">0.649***</td><td rowspan="2">0.670***</td><td>0.764***</td><td rowspan="2">0.011</td></tr>
<tr><td>Debt is a slight burden</td><td>0.012</td></tr>
<tr><td>Housing costs are a heavy burden</td><td>2.372***</td><td>2.533***</td><td>1.505***</td><td rowspan="2">1.481***</td></tr>
<tr><td>Housing costs are a slight burden</td><td>0.701***</td><td>0.983***</td><td>0.003</td></tr>
<tr><td>Outright owner</td><td>Reference</td><td>Reference</td><td>Reference</td><td>Reference</td></tr>
<tr><td>Owner paying mortgage</td><td>0.21</td><td>0.419***</td><td>0.324***</td><td rowspan="2">0.1</td></tr>
<tr><td>Tenant</td><td>0.797***</td><td>0.759***</td><td>0.778***</td></tr>
<tr><td>≥ 1 adult has other country of birth</td><td>0.267*</td><td>0.275</td><td>0.576***</td><td>X</td></tr>
<tr><td>Household with dependent children</td><td>-0.189</td><td>-0.243*</td><td>-0.187*</td><td>-0.490***</td></tr>
<tr><td>Number of adults in household</td><td>-0.123*</td><td>0.04</td><td>0.034</td><td>-0.049</td></tr>
<tr><td>Number of children in household</td><td>0.05</td><td>0.053</td><td>0.004</td><td>0.308***</td></tr>
<tr><td>Post-secondary/tertiary</td><td>Reference</td><td>Reference</td><td>Reference</td><td>Reference</td></tr>
<tr><td>Upper secondary</td><td>0.268**</td><td rowspan="2">0.633***</td><td>0.455***</td><td rowspan="2">0.908***</td></tr>
<tr><td>Lower secondary or below</td><td>0.839***</td><td>1.055***</td></tr>
<tr><td>Low work intensity household</td><td>0.529***</td><td>0.905***</td><td>0.417***</td><td>X</td></tr>
<tr><td>≥ 1 adult is unemployed</td><td>0.795***</td><td>0.802***</td><td>0.707***</td><td>X</td></tr>
<tr><td>≥ 1 adult is retired</td><td>-0.142</td><td>0.116</td><td>-0.247***</td><td>-0.185*</td></tr>
<tr><td>Region 1</td><td>Reference</td><td>Reference</td><td>Reference</td><td>Reference</td></tr>
<tr><td>Region 2</td><td>0.083</td><td>-0.132</td><td>0.737***</td><td>0.108</td></tr>
</table>

Variable of interest	Austria	Czechia	Italy	Bulgaria
Region 3	-0.081	-0.313*	0.443***	–0.081
Region 4		0.077	-0.101	
Region 5		-0.440***	0.095	
Region 6		-0.162		
Region 7		-0.216		
Region 8		-0.106		
Observations	13 067	17 589	42 623	11 803
MacFadden's R^2	0.1806	0.1714	0.1525	0.0900

Note: Estimations using Stata (ordered logit). Standard errors estimated using survey design variables following Goedemé (2013). Countries ranked according to highest percentage of zero deprivations.

**, p < 0.10; **, p < 0.05; ***, p < 0.01.*

Cells marked with X indicate that variable is omitted because of low variation in variable (i.e. cell size below 100 within either the subpopulation with zero deprivations or the subpopulation with one or more deprivations). For the same reason we have merged categories of variables for certain countries (identifiable by merged cells in above table).

Reading note: A one-unit increase in income (1 000 PPS) reduces an Austrian's ordered log-odds of having a higher level of MSD by 0.067 while the other variables in the model are held constant.

Source: Authors' computations, UDB September 2017.

8.3. Impact of an additional transfer on the level of material and social deprivation

We illustrate our method by estimating the effect of a very small universal transfer of EUR 150 (in PPS) per year ([125]). This hypothetical transfer represents about 1 % of the equivalised median annual income in the EU-SILC data. Because the MSD scale is the same across countries, we use the same (absolute) amount for the marginal effect analysis ([126]).

Our method of impact estimation involves a comparison of the **predicted** MSD distribution using current household disposable income with that of the **predicted** distribution using income after the small additional transfer ([127]). The difference between these distributions reflects the estimated impact. The impacts presented have been obtained through country-level ordered logit regressions (see Section 8.2), predicting the probabilities of deprivation before and after the small additional transfer.

We present in this section what this implies for the EU's official MSD rate, which counts persons as deprived if they have five or more deprivations. Our results show that a EUR 150 universal transfer would have a very small effect on the MSD rates in Europe's richest countries (Nordic countries, Switzerland, Luxembourg, the Netherlands and Austria), but in the other countries the reduction in rates would be non-negligible: it ranges from 0.08 p.p. in the United Kingdom to 1.04 p.p. in Romania (Figure 8.3A). In total, this small amount of transfer would reduce

([125]) In our data, individuals are the unit of analysis (row). As household income is equivalised, if 150 PPS were added to each row, the amount of transfer a household would receive in reality would vary with the household composition: a family consisting of two adults and two children would receive 315 PPS (150 × 2.1) while a single adult person would receive 150 PPS (150 × 1).

([126]) One could finance such a transfer, for instance, through a tax paid by wealthy European residents whose probability of MSD is zero. In this exercise, however, we do not take account of the tax collection side, meaning that we add 150 PPS to the disposable income of the wealthy too. As this tax would fall on residents who have a close to zero probability of deprivation, this simplification is unlikely to affect the impact estimates.

([127]) Using Stata's default post-estimation syntax 'predict'. This syntax predicts, for each person, the probabilities of being observed in each of the deprivation values (the probability of deprivation values 0 to 13, with these probabilities adding up to 1 at the individual level). Following Cameron and Trivedi (2010, p. 528), the predicted deprivation distribution is the mean probability of each deprivation value in the weighted sample.

the number of materially deprived Europeans (EU countries only) by about 876 000 persons.

Figure 8.3B shows the average number of deprivations in each country included in Figure 8.3A, which is a proxy of their standard of living. There is a negative correlation between the impact on the MSD rate and the countries' standard of living. In the most deprived countries, the decline is the largest. Yet the correlation between the impact on the MSD rate and average living standards (Figure 8.3A and B) is far from perfect, which suggests that other societal forces play a role as well.

The impact on deprivation is first explained by the country's ordered logit regression income coefficient (i.e. the association between deprivation and income), although the marginal effect in a non-linear regression model depends not only on a person's income level but also on their other characteristics (and thus on all regression coefficients). This association is, for example, stronger in Romania than in Bulgaria; hence the larger reduction in deprivation in Romania than in Bulgaria in Figure 8.3A.

In this chapter, one can think of the national-level coefficients of the ordered logit regression model as 'summarising' the collective effect of societal forces on MSD. Public policy and social policy are some of the societal factors that could also explain differences between countries in the impact on the MSD rate. Another important and potentially interrelated explanatory factor is the nature of the domestic economy and its interactions with other economies. Finally, differences between countries in the EU-SILC data collection and data preparation could also play a role.

A scaled-up universal transfer of 1 500 PPS would lead to close to proportionate decreases in the EU's official MSD rate, with reductions from close to 1 p.p. in the United Kingdom, through 5 p.p. in Bulgaria, Greece and Hungary, to over 10 p.p. in Romania (hence a reduction in the MSD rate from 50 % to 40 %). In absolute numbers, the transfer would reduce the number of materially deprived persons (EU only) by about 8.6 million. As recalled earlier, it is also important to keep in mind that the analysis makes the assumption that there are no behavioural changes, that is, transfer recipients make the same choices (with respect to work, care and spending) with or without the additional amount of transfers. This is considerably less plausible with a 1 500 PPS transfer than with a 150 PPS transfer.

In the scenario described, namely that of a small universal EU-wide transfer, the costs of such a scheme would amount to about 1 % of average social spending in the EU, or close to 30 % of the EU's 2015 budget. Expressed as a percentage of national social spending, the costs of such a transfer would be considerably larger for about half of those countries, reaching 3–3.5 % for Latvia, Serbia, Bulgaria and Romania (Figure 8.4).

Instead of a universal transfer, the costs of targeted transfer schemes designed to reach those with either at least one or at least five deprivations would be lower. At EU level, the costs of a scheme targeted at persons with at least one deprivation amount to about 0.57 % of current social spending. The costs of a scheme targeted at those experiencing five or more deprivations would be 0.18 %. In terms of the EU's 2015 budget, the costs of the targeted schemes would be 16.4 % and 5 % respectively (compared with 30 % for the universal scheme).

Cost differences between universal and targeted schemes depend on the average living standard of the country. In countries with higher living standards and thus fewer people experiencing high deprivation, the cost differences between the universal and targeted schemes are much larger than for countries with lower living standards.

The calculations in this section are only rudimentary, and serve to illustrate what types of analyses become feasible with the methodology developed in this chapter. We assumed, for instance, that the programme delivery costs of a universal scheme would be 5 % of total programme expenditure, whereas they would be 15 % for both targeted schemes, as a targeted programme is more costly administratively. The administrative capacity and thus costs would most likely vary by country (Notten and Gassmann, 2008). We further made the rather implausible assumption that countries' administrations would accurately identify their residents' deprivation status. A failure of the assumption has implications for both the estimated programme costs and effects on deprivation (Notten and Gassmann, 2008).

Figure 8.3A: Reduction in MSD rate after 150 PPS transfer, 2015

(p.p.)

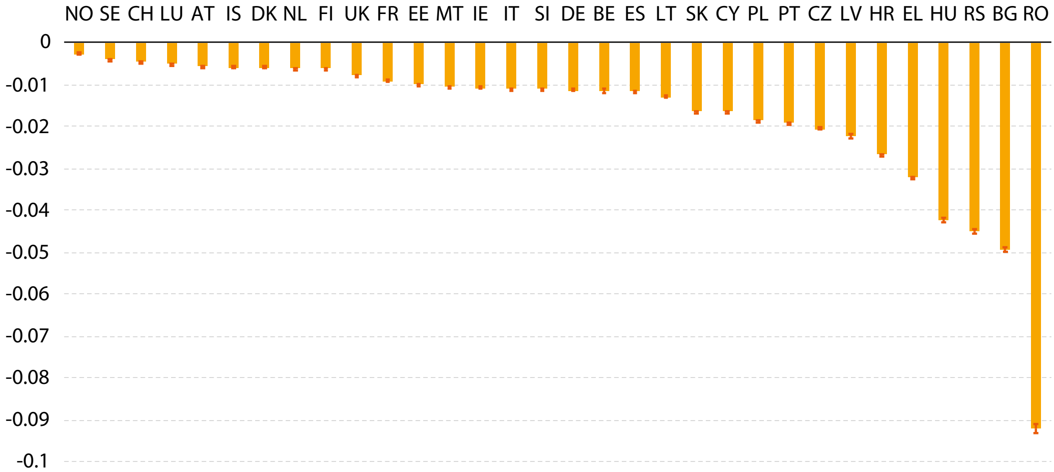
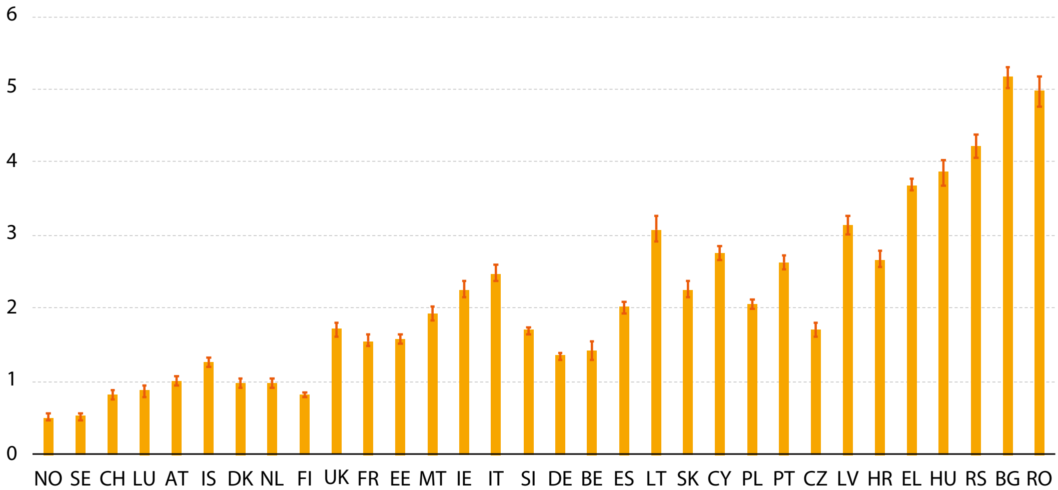


Figure 8.3B: Average number of deprivations by country, 2015

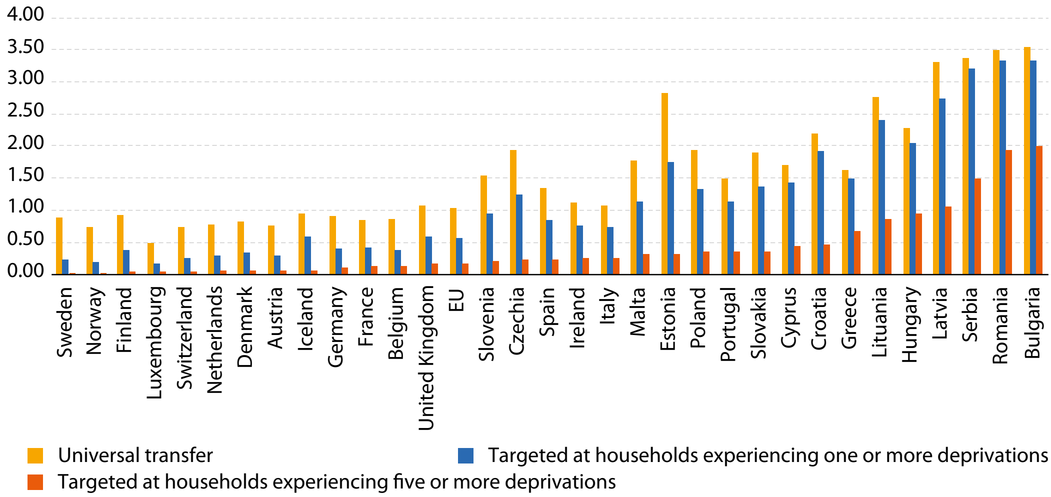


Note: See Appendix 2 for a list of country abbreviations, countries ranked by reduction in MSD rate after 150 PPS transfer. Unit of analysis: individuals. Persons count as materially deprived when they have five or more deprivations.

Reading note: In Romania, the proportion of people materially deprived (i.e. suffering from at least five deprivations) would decrease after a 150 PPS transfer by 1 p.p. Romania has the second highest average number of deprivations.

Source: Authors' computations, UDB September 2017.

Figure 8.4: **Transfer spending as a percentage of total social spending, 2015**
(%)



Note: Countries are ranked according to the level of spending required when targeted at deprived people.

Reading note: In Lithuania, the cost of a 150 PPS scheme targeted at persons with at least five deprivations amounts to slightly less than 1 % of current social spending.

Source: Authors' computations, UDB September 2017. Population (2015) and social spending statistics (2014) available on the Eurostat website.

8.4. Conclusion

The AROPE population has not decreased sufficiently to meet the 2020 target in EU countries. It is therefore important to evaluate the role and effectiveness of the policies adopted to combat income poverty and social exclusion in Europe. This chapter is based on our 2020 paper, which developed an approach to estimate the effect of additional transfers on material deprivation. It illustrates this approach with reference to the 32 countries covered in EU-SILC and the new MSD indicator. This approach complements established methods that use income to evaluate the impact of social transfers on income poverty at EU level (see Chapter 7 of the present volume).

This chapter uses ordered regression models to predict the MSD distribution and to calculate the impact of a small additional income transfer (150 PPS) across all 32 EU-SILC countries.

It shows that a universal 150 PPS transfer per year would reduce the number of persons with five or more deprivations in the EU by 876 000, whereas a 1 500 PPS transfer would reduce that number by 8.6 million. The impact of extra transfers on the MSD rate is higher in the most deprived countries, which highlights the importance of targeted investment.

The costs of such a universal additional transfer of 150 PPS are modest when expressed as a share of average social spending in the EU, but they are considerable for some EU Member States with lower spending levels (i.e. 3–3.5 % of social spending in Latvia, Bulgaria and Romania) and would represent a large investment in terms of the EU's current budget. However, when targeted at the most deprived people in each country, these costs are substantially reduced. In terms of the EU's budget, the costs of a scheme targeted at people experiencing at least five deprivations would represent 5 % (compared with 30 % for the universal scheme).

The results presented in this chapter show that the impact of social transfers on material deprivation is higher when standards of living are lower, an effect that is present both within and across countries and underlines the importance of a progressive social transfer system at national level and targeted EU investment at EU level (see Notten and Guio, 2020, for more details). Concluding, the method developed by Notten and Guio (2020) and briefly illustrated in this chapter is the first to allow the computation of population-level impact estimates of the impact of additional social transfers on MSD rates for 32 European countries, using reasonably comparable data (the best available) and using a reasonably comparable estimation methodology. It represents significant methodological progress in developing and testing available tools to measure the impacts of a very influential policy instrument in Europe's societies on a social and politically valued aspect of people's well-being. This method has broader applicability and could be used to measure the impact of extra social transfers on other non-monetary dimensions of social exclusion, such as housing deprivation, energy poverty and overindebtedness. Further research can expand on this new knowledge by testing the tools in settings expected to yield more accurate impact estimates (e.g. as part of microsimulation models such as Euromod) and/or in settings where there is scope for establishing a better counterfactual using advanced regression-based analyses of treatment effects, such as the difference-in-difference and regression discontinuity models. This research also highlights the importance of continuous efforts to improve the EU-SILC data to capture differences in national contexts, while also making progress on cross-national comparability. Without such improvements, we cannot expect to make progress in our understanding of the role of a country's policies on the well-being of its residents.

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9 Threshold sensitivity of income poverty measures for EU social targets

Rolf Aaberge, Andrea Brandolini and Iryna Kyzyma ([128])

9.1. Introduction

In 2010, the Europe 2020 strategy set a social inclusion target of reducing the number of people who are AROPE by at least 20 million by 2020 (Frazer et al., 2010; Chapter 1 in this volume). The AROPE indicator counts all people suffering from deprivation in at least one of three dimensions: household income, material endowment and work intensity. Apart from identifying these relevant dimensions, this indicator has two distinctive features. First, it is a 'head count' measure: in each dimension, it relies on the arbitrary choice of a threshold (e.g. 60 % of the median equivalised disposable income) and ignores the severity of individual conditions relative to the threshold (Sen, 1976). Second, it is a 'union-type multidimensional' measure: it reflects the spreading of hardship but is insensitive to the number of deprivations suffered by each individual and their cumulative effects (Atkinson, 2003; Aaberge and Brandolini, 2015).

These features of the AROPE indicator provide a clear operational meaning to the policy target of the Europe 2020 strategy. Yet a little recognised facet is that this approach implies a well-defined, but debatable, policy prescription on the optimal allocation of a (limited) anti-poverty budget.

Let us take a single dimension, say income. Bourguignon and Fields (1990) suggested that the policy that maximises poverty reduction when poverty is measured with the head count index is to transfer the given budget to the richest among the poor: one starts by raising the income of the richest of the poor to the poverty threshold, then the second richest and so on. They labelled this allocation 'r-type policy'. By contrast, with a measure of poverty that is sensitive to the intensity of the poverty condition (more formally, one that satisfies the Pigou–Dalton principle of transfers among the poor), the optimal allocation would target the poorest individuals first, and raise their income to the minimum level allowed by the anti-poverty budget. They named this allocation 'p-type policy' ([129]). Since the income component of the AROPE indicator is a head count measure, the maximum reduction of income poverty obtains when the anti-poverty budget concentrates on the richest among the poor. If strictly implemented, this r-type policy would help progress towards the Europe 2020 target but would be also hard to justify from an ethical point of view, since poverty is arguably more severe the poorer a person is.

Multidimensionality raises additional questions, as the optimal allocation of the anti-poverty budget implies choosing how to distribute resources not only among people, but also across dimensions. The allocation decision depends on the interaction between the social weight attributed to each dimension in the multidimensional poverty index

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([129]) More generally, Bourguignon and Fields (1990, 1997) demonstrated that the degree of inequality aversion determines whether the composite head count and distributive-sensitive measure produces a p-type policy, an r-type policy or a mixture of them.

and its corresponding price that is the amount of money necessary to lift somebody out of deprivation. For instance, if '(enforced) lack of a television set' is one of the deprivation dimensions, the cost of a television set is the price to attach to such deprivation. The SMD indicator, one of the three AROPE constituents, is a multidimensional index that assigns equal weights to the nine necessities it considers: the allocation minimising the number of deprived people would then compute the minimum transfer required to lift individuals out of SMD based on the prices of these necessities only, and would subsidise those needing less money first, as discussed earlier. In fact, such mechanical application would misconstrue the nature of this deprivation indicator, which is meant to capture an underlying latent variable rather than represent specific forms of deprivation to be directly addressed one by one ([130]). Yet this example illustrates that the optimal pro-poor policy defined on the basis of a head count multidimensional index would prioritise the individuals who need less money to be lifted out of poverty, given the structure of social weights, and hence would often target the cheapest dimensions. Favouring the least disadvantaged people relative to those suffering from multiple, and more costly, deprivations would again be an ethically disturbing policy choice.

Our purpose in this chapter is to reconsider poverty measurement and the associated anti-poverty allocation in Europe by tackling the first problem identified earlier, the strict requirements of head count measures, while leaving the issues concerning union-type multidimensional indices to future research ([131]). We address the two features of head count measures mentioned above – the arbitrariness of the choice of the threshold and the insensitivity to the severity of poverty – by considering two families of threshold-free poverty measures proposed by Aaberge and Atkinson (2013). These measures are based on the intuition that any income value below the median is an acceptable poverty line, the median being the watershed between the poor and the non-poor. One family of measures focuses on the number of poor people and is a weighted average of head count ratios, whereas the other family focuses on how poor those people are and is a weighted average of relative poverty gaps. In both cases, the weights reflect the severity of poverty. Besides, both measures allow for a free parameter k that captures the aversion to poverty depth: the higher the value of k, the more weight is assigned to the poorest and the less weight is given to head counts and poverty gaps defined by high median-based poverty lines. Although each measure returns a complete ordering, the parameter k allows for different value judgements. These measures always favour p-type policies (for $k > 1$).

The chapter is organised as follows. In Section 9.2 we consider the definition of poverty thresholds and introduce the threshold-free primal and dual measures of poverty, sketching their implications for the optimal allocation of an anti-poverty budget. In Section 9.3 we describe the data, which are drawn from EU-SILC, and the estimators used in the empirical analysis. In Section 9.4 we report poverty estimates based on the standard AROP rate (see Chapter 1 in this volume) and 10 alternative threshold-free poverty measures for the 28 Member States of the EU in 2018. In Section 9.5, we discuss how these alternative poverty measures affect the optimal allocation of an anti-poverty budget and, in turn, change as a consequence of implementing such a policy. We draw the main conclusions in Section 9.6.

9.2. Threshold-free primal and dual measures of poverty

In his insightful Walras–Bowley lecture, Atkinson (1987, p. 750) observed that 'It has been recognised since the early days that there is room for differences of view as to the drawing of the line'

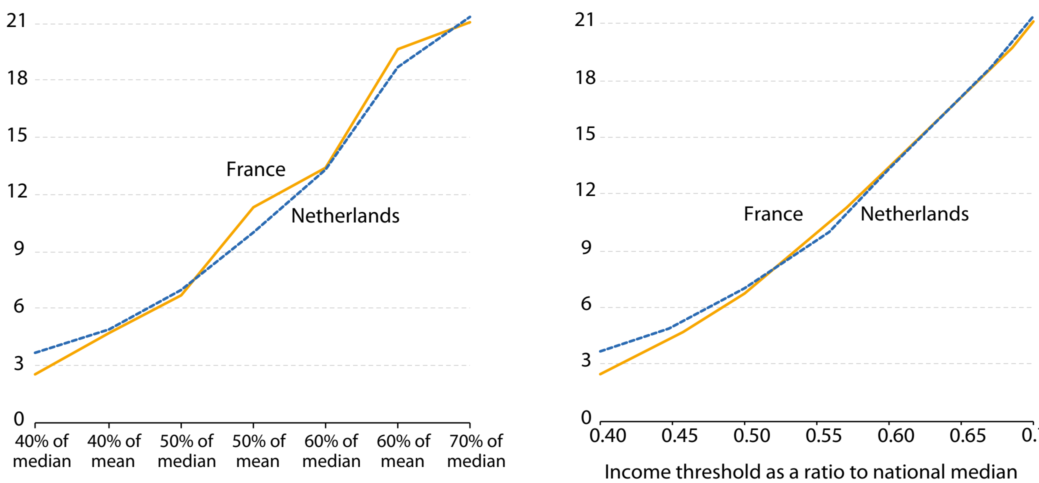
([130]) As one editor remarked to us, ideally policy should aim to provide the additional resources required to bring households to the point where they can afford the minimum adequate living standard, as gauged by the basket of necessities included in the indicator. It should also be noted that, despite the equal weighting assumed in the SMD indicator, people appear to have a clear order of necessities: when facing difficulties, they tend to cut back on holiday expenditure first, then they reduce savings for unexpected expenses, and finally they contract expenses for food and housing (e.g. Deutsch et al., 2015; Guio and Pomati, 2017).

([131]) Aaberge and Brandolini (2015) provide methodological considerations on the SMD indicator.

and suggested that a straightforward solution might be comparing the cumulative distribution over a range of permissible poverty lines. Since results from stochastic dominance may be difficult to communicate to the public, a crude alternative might be to calculate statistics for several poverty thresholds. Accordingly, Eurostat releases poverty ratios for seven thresholds: 40 %, 50 %, 60 % and 70 % of the median equivalised disposable income, and 40 %, 50 % and 60 % of the mean equivalised disposable income. However, utilising multiple thresholds at the same time may not facilitate communication either. This is shown in Figure 9.1, which shows the poverty rates for these different thresholds for France and the Netherlands in 2018.

With the standard AROP threshold set at 60 % of the median equivalised income, poverty incidence is virtually the same in the two countries (13.3 % in the Netherlands and 13.4 % in France). As the threshold varies, results change too: at 40 % of the median, the Dutch poverty rate exceeds the French one by more than 1 p.p., while the opposite happens at 50 % of the mean (Figure 9.1, left-hand panel). Thus, not only the size but also the sign of poverty differences changes. In fact, differences appear to narrow when we re-express the mean-based thresholds as ratios to the respective national medians (Figure 9.1, right-hand panel) ([132]). Yet the (interpolation) lines still cross, and the difference at the bottom remains. Clearly, country rankings, as well as temporal comparisons, are sensitive

Figure 9.1: Poverty rates in France and the Netherlands for different poverty thresholds, 2018
(%)



Reading note: In the Netherlands the poverty rate when the threshold is set at 40 % of the national median is 3.7 % compared with 2.5 % in France. The horizontal axis shows thresholds in a discrete manner in the left-hand panel and on a continuous line in the right-hand panel. In the latter, mean-based thresholds are re-expressed as ratios to their respective national medians, so that in France 40 % of the mean corresponds to 46 % of the median and so forth.

Source: Authors' computations on data from the Eurostat database (https://ec.europa.eu/eurostat/data/database) and EU-SILC surveys (ilc_li01, ilc_li02), downloaded on 2 November 2020.

([132]) Note that this evaluation remains in the framework of relative income comparisons. If we plotted the Dutch poverty rates against thresholds expressed as ratios not to the Dutch but to the French median, the Dutch interpolation line would move rightwards, as household incomes are, on average, higher in the Netherlands than in France. This 'real-income' comparison would show that poverty incidence tends to be lower in the Netherlands than in France when a common poverty standard is used.

to the arbitrary choice of the poverty line. On the other hand, to the extent that the interpolation of these seven discrete points is acceptable, this procedure may be seen as an approximation of a stochastic dominance analysis, which reveals that the outcome may be a partial rather than complete ordering.

Aaberge and Atkinson (2013) propose a general approach that avoids the arbitrariness of choosing a specific poverty threshold. First, they suggest that there is no reason to set the poverty threshold beyond the median M whenever poverty is a minority phenomenon. The median is the 'watershed' in poverty measurement ([133]). Second, they accept that all income levels below the median could be chosen as poverty thresholds, provided that they are considered together not singly, and hence average out all the corresponding head count measures. Third, they allow for the severity of the poverty condition by assigning a weight that reflects how much each of these poverty thresholds falls short of the median. This leads to the family of *primal measures* Ψ_k, which is defined by

$$\Psi_k = k\int_0^1 (1-z)^{k-1} F(Mz)dz = \frac{k}{M}\int_0^M \left(\frac{M-x}{M}\right)^{k-1} F(x)dx = \int_0^M \left(1-\frac{x}{M}\right)^k dF(x),\ \ k \geq 1, \quad (9.1)$$

where $x = Mz$ indicates income and $F(x)$ its cumulative distribution function, and k is a free parameter capturing aversion to severity of poverty. The middle term on the right shows that the primal measures Ψ_k are weighted averages of head count measures $F(x)$ calculated for any value x below the median, where the weight is a power function of the relative distance of x from the median M, $(1 - x / M)$. The parameter k allows for the differentiation of the weighting structure in order to capture different concerns for the severity of poverty: as k rises, Ψ_k become more sensitive to income changes that affect the poorest people. Integration by parts yields the last term on the right, which shows that the class of primal measures Ψ_k coincides with the class of poverty indices proposed by Foster, Greer and Thorbecke (1984), known as the FGT index, with the poverty threshold set at the median. The conceptual foundation is rather different, however, since the primal measures arise from the idea of averaging out poverty rates for all the possible thresholds below the median, whereas the FGT index was motivated by the search for a subgroup of decomposable measure.

The reasoning underlining the primal measures could be reversed: rather than focusing on shares of people weighted by their income shortfall, we could focus on income shortfalls weighted by the share of people. Formally, this means choosing a different independence axiom. In practice, it results in the family of *dual measures* Π_k defined by

$$\Pi_k = k\int_0^{1/2} (1-2t)^{k-1}\left(1-\frac{F^{-1}(t)}{M}\right)dt$$
$$= 2^{k-1}k\int_0^M \left(\frac{1}{2}-F(x)\right)^{k-1}\left(1-\frac{x}{M}\right)dF(x),\ \ k \geq 1, \quad (9.2)$$

where $t = F(x)$ denotes the share of population with income not greater than x, and k is a free parameter that captures, as before, the concern for the severity of poverty. The dual measures are averages of people's proportionate income shortfalls, $(1 - x / M)$, an indicator of the severity of their poverty status, weighted by (a power function of) the share of people who are closer to the median than they are $(0.5 - F(x))$: the larger the proportion of people who are richer than a poor individual, the higher the weight the measures assign to this poor individual (for $k > 1$). As for primal measures, the average is taken over the population with income below the median.

Both families of measures do not rely on a specific threshold and satisfy a modified version of the Pigou–Dalton principle of transfers, called mean–median, preserving across-median progressive transfers. Both Ψ_k and Π_k vary between 0, which occurs when all individuals below the median receive the median income, and 0.5, which is attained when they all have nil income. Note that the range [0,0.5] differs from the original normalisation [0,1] used by Aaberge and Atkinson (2013).

([133]) In principle, a different watershed could be used, for instance replacing the median with some fraction of it. Analytical expressions of poverty indices would become more cumbersome. More importantly, this alternative watershed would lose the natural appeal of the median as the value that divides the population into two halves, which is an attempt to overcome the arbitrariness of threshold definitions.

Where $k = 1$, the primal and dual measures coincide and are given by

$$\Psi_1 = \Pi_1 = \int_0^M \left(1 - \frac{x}{M}\right) dF(x) = \frac{1}{2}\left(1 - \frac{\mu_M}{M}\right), \qquad (9.3)$$

where $\mu_M = E(X \backslash X \leq M)$ is the average income of the bottom half of the population. This is the relative poverty gap (half the income gap ratio) in the case where the median M is the threshold. As clear from the middle term in equation (9.1), this index can be interpreted as the simple average of the head count measures $F(x)$ calculated for any poverty threshold x between 0 and M. It falls as μ_M rises and is insensitive to the way incomes are distributed below the median.

For $k > 1$, the primal and dual measures differ, but are all sensitive to below-median income distribution. The primal measure for k=2 yields the squared poverty gap:

$$\Psi_2 = \int_0^M \left(1 - \frac{x}{M}\right)^2 dF(x) = 2\Psi_1^2 + \frac{\sigma_M^2}{2M^2}, \qquad (9.4)$$

where $\sigma_M^2 = var(X \backslash X \leq M)$. Equation (9.4) shows that Ψ_2 falls with increasing mean income μ_M and decreasing income dispersion σ_M^2. Thus, Ψ_2 diminishes if incomes below the median rise or become less unequally distributed. The k=2 case of the dual approach leads to

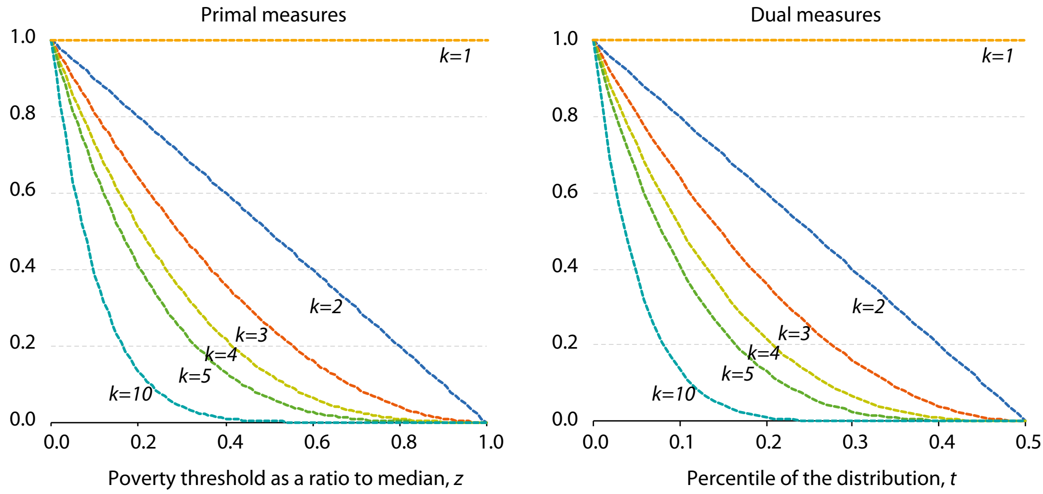
$$\Pi_2 = 4\int_0^M \left(\frac{1}{2} - F(x)\right)\left(1 - \frac{x}{M}\right) dF(x)$$

$$= \frac{1}{2}\left(1 - \frac{\mu_M}{M}\right) + \frac{\mu_M}{2M} G_M = \Pi_1 + \left(\frac{1}{2} - \Pi_1\right) G_M, \qquad (9.5)$$

where $G_M = 1 - \frac{4}{\mu_M}\int_0^M (1 - 2F(x))\, x dF(x)$ denotes the lower-tail Gini coefficient, that is, the Gini coefficient of the conditional distribution of X given that $X \leq M$. Note the Π_2 measure coincides with the asymptotic version of the poverty measure introduced by Sen (1976) when the poverty line is equal to M. The first term of Π_2 is the relative poverty gap and captures the extent to which the average income of the bottom half of the population falls short of the median, while the second term measures the contribution from the unequal distribution of incomes below the median as measured by the Gini coefficient multiplied by half the ratio of the mean income below the median to the median.

In both primal and dual measures, a crucial role is played by weights. If we interpret the negative of these measures as the social welfare function implicit in the poverty assessment, weights represent the marginal valuation of income: they indicate by how much social welfare changes after raising income by a small amount. In the primal measures Ψ_k, the weight $(1 - z)^{k-1}$ assigned to the head count for the poverty threshold Mz corresponds to the marginal valuation of an individual who has income $x = Mz$. Likewise, in the dual measures Π_k, the weight $(1 - 2t)^{k-1}$ assigned to the income shortfall at the percentile t corresponds to the marginal valuation of an individual who has income $x = F^{-1}(t)$ for $0 \leq t \leq 0.5$. The marginal valuation of income is a decreasing function, whose steepness depends on the parameter k: the higher k, the more rapidly the marginal valuation falls with income. This is shown in Figure 9.2, which plots the weights separately for the two families of measures. (For a given value of k, the shapes of the curves are the same, but notice that z varies between 0 and 1, while t varies between 0 and 0.5.) Taking primal measures as example, the marginal valuation of income at 2 % of the median is 1.1 times that at 10 % of the median for $k = 2$; this ratio quickly rises to 1.4 for $k = 5$ and 2.2 for $k = 10$. When k is large, people located close to the median provide a negligible contribution to measured poverty, whereas those far below have a substantial impact. In the remainder of this chapter, we consider five values of the parameter k (1, 2, 3, 4 and 5). We exclude higher values, since they would imply very extreme weighting structures (as shown by the curves for $k = 10$).

Figure 9.2: **Weights for primal and dual poverty measures based on various *z*, *t* and *k* values**



Note: *k* is a degree of distribution sensitivity used to calculate the measures of poverty.

Reading note: The weight corresponding to $z = 0.2$ (or 20 % of the median) and $k = 2$ is 0.8 (left panel), whereas the weight corresponding to $t = 0.1$ (or the 10th percentile of the distribution) and $k = 5$ is 0.41 (right panel).

Source: Authors' computations.

With regards to the optimal allocation of an anti-poverty budget, any allocation is optimal for the relative poverty gap $\Psi_1 = \Pi_1$, since the mean income of the bottom half of the population is insensitive to who among the poor receives the transfer. Conversely, Ψ_k and Π_k for $k > 1$ are sensitive to the distribution of transfers among the poor and assign the largest weight to the poorest among the poor ([134]). As a result, the policy that maximises poverty reduction is to bring the poorest of the poor to the highest possible post-intervention minimum income level.

([134]) Bourguignon and Fields (1990) conclude that any optimal allocation (p-type, r-type or mixed) is consistent with the asymptotic version of the Sen index. This is due to the role played by the head count. Aaberge and Atkinson's (2013) dual measure coincides with the Sen index when the poverty line is equal to the median (head count equal to 0.5) and hence does not suffer from the discontinuity created by poverty lines that are lower than the median. For this reason, unequivocally supports only the p-type policy.

9.3. Data and statistical analysis

In our empirical analysis, we rely on cross-sectional data from the 2018 wave of EU-SILC (UDB March 2020). We focus on the 28 countries constituting the EU in 2018, hence including the United Kingdom. The income variable is the household equivalised income $x_i = y_i / e_i$ (HX090), where household's i total disposable income is divided by the number of equivalent adults e_i (see Chapter 2 in this volume for further details). The reference year for the income variable is the calendar year prior to the survey year, except for the United Kingdom (survey year) and Ireland (12 months preceding the interview). Negative income values are recoded to 0. All poverty measures reported in this chapter are calculated using cross-sectional individual weights (RB050) or cross-sectional household weights (DB090) as appropriate. The weights are normalised so that they add up to 1 for the entire population (sample).

We estimate income poverty ratios with both the AROP rate and the primal and dual measures for five different values of aversion to the severity of poverty. The estimator of the AROP rate is the percentage of individuals living below the poverty threshold set at 60 % of the median M of the personal distribution of disposable equivalised household income in their own country,

$$\text{AROP rate} = \sum_{\{i: x_i < 0.6M\}} w_i \,, \qquad (9.6)$$

where w_i is the individual weight. The estimators of the primal and dual income poverty measures are given by

$$\Psi_k = \sum_{\{i: x_i \le M\}} \left(1 - \frac{x_i}{M}\right)^k w_i, \; k = 1, 2, \ldots, 5, \qquad (9.7)$$

and

$$\Pi_k = k \sum_{\{i: x_i \le M\}} \left(1 - 2 \sum_{\{j: x_j \le x_i\}} w_j\right)^{k-1} \left(1 - \frac{x_i}{M}\right) w_i, \; k = 1, 2, \ldots, 5. \; (9.8)$$

An individual is considered poor if his or her equivalised income falls below the poverty threshold z. With the AROP indicator in equation (9.6), z is 60 % of the median. With the threshold-free primal and dual measures, z spans the range between 0 and 1: in the primal measures, equation (9.7), the poverty status of each individual is defined for each threshold and then aggregated across all people whose income does not exceed the median; in the dual measure, equation (9.8), it is the relative income shortfall, compared with the median, to be aggregated over the same group of people.

9.4. Poverty across Member States in 2018

We present our poverty estimates based on all selected indices for all EU countries in 2018, together with the ensuing country ranking, in Table 9.1. A few comments are in order.

First, the AROP rates and the primal and dual measures with $k = 1$ are rather closely aligned and of similar sizes, although the primal and dual measures vary over a narrower range. Since the primal measure is the simple average of head count ratios calculated taking any fraction of the median as a possible threshold, we could be brought to infer that the choice of the poverty threshold has a relatively minor impact. Yet the ranking of countries is sensitive to the choice of either measure. It remains unchanged for only seven countries. For most other countries the change is at most two positions either up or down, but for a few it is more marked. Moving from the AROP rate ranking to the one based on $\Psi_1 = \Pi_1$, Ireland, France, Malta and Slovenia move up by three positions, while Hungary loses six positions, sliding down from 5th to 11th. In general, this evidence suggests that the sensitivity of income poverty statistics to the choice of the poverty threshold varies across countries, which might also have an impact on their ranking.

Second, the ranking of countries is also sensitive to the value of k, the discrepancy being quite large for some countries. The higher the value of k, the more sensitive the primal and dual measures of poverty become to the share of individuals in deep poverty (those with incomes far below the median). If a country ranks high according to the primal measure of poverty with a low value of k, but worsens its position by taking a higher k, this country must have a substantial portion of the poor with incomes far below the median: see, for example, Slovakia, whose ranking drops from 2nd to 10th when k changes from 1 to 5. Conversely, if a country ranks relatively low with the primal measure Ψ_1, but improves its position with Ψ_5, a substantial portion of the poor in this country must have an income relatively closer to the median: this is the case of Belgium, which changes its position from 15th to 8th. In few countries, ranks remain stable as k increases (e.g. Czechia and Romania, which rank 1st and last regardless of the value of k). However, most countries move up and down the ranking ladder as k varies, sometimes significantly.

Third, the rankings based on dual measures are somewhat less sensitive to the values of k than those based on the primal measures. The origin of this difference becomes apparent comparing equations (9.4) and (9.5): the distributive term is the squared coefficient of variation in Ψ_2 but the less tail-sensitive Gini coefficient in Π_2 [135]. Although the

[135] The absolute Gini coefficient was originally introduced in astrophysics as a robust alternative measure of dispersion to the variance.

ranking remains unchanged for all values of k only in three countries (Czechia, Romania and Sweden), in most other countries it changes by at most three positions up or down. The exceptions are Cyprus (which moves up five steps as k changes from 1 to 5), Belgium, Estonia and Malta (up four steps) and Italy and Slovakia (down four steps). Equation (9.5) shows that the contribution from the distributive terms is $\Pi_2 - \Pi_1 = (0.5 - \Pi_1)G_M$. Accounting for the unequally distributed incomes below the median (i.e. considering Π_2 instead of Π_1) raises measured poverty by 35–38 % in 24 out of 28 countries.

Overall, the correlations between the country rankings produced by the selected poverty measures are high and statistically significant, as shown by the Spearman paired correlation coefficients reported in Table 9.2. The table confirms that the ranking of countries is more robust for dual than for primal measures of poverty and shows that the dual measures are also slightly more correlated with the AROP rate. The smallest correlation between the AROP rate and the primal and dual measures is found for $k = 5$, that is, for the indices that are most sensitive to the severity of poverty, hence to the distribution of incomes below the median. This evidence implies that country rankings are overall quite robust to the measure of income poverty used. There may be deviations in the ranking order, but they are relatively small for most countries.

The fact that country ordering is only moderately affected by the choice of the poverty index is reassuring, but the index values are also of interest. In particular, how is the extent of measured poverty going to change as we select a different index? We may return to the comparison between France and the Netherlands. The AROP rates that we calculated for Table 9.1 are the same as those drawn from the Eurostat website reported earlier: 13.4 % and 13.3 % respectively. The threshold-free measures considered in this chapter consistently reverse the country order and suggest that poverty levels are higher in the Netherlands than in France, by 5 % to 72 % with the primal measures and by 5 % to 7 % with the dual measures (Figure 9.3). This result is not surprising. As has been seen, the share of very poor people, that is those with an equivalent income lower than 40 % of the median, is noticeably higher in the Netherlands than in France. This feature is captured by the primal and dual measures, which consider the whole distribution below the median; and the more so for high values of k, which yield the measures most sensitive to the distribution at the bottom.

The impact of the bottom of the distribution on primal and dual measures shows up in their higher correlations with the poverty rate calculated with a threshold set at 40 % of the median than with the standard AROP rate. For instance, the correlation coefficients for Ψ_5 are 0.883 with the former and 0.869 with the latter, and the corresponding values for Π_5 are 0.918 and 0.926 (these coefficients are calculated on the index values rather than the ranks as in Table 9.2). The range of values spanned by dual measures across countries is narrower than that of primal measures. For dual measures the difference between maximum and minimum values varies between 43 % and 47 % of the mean; for primal measures the same difference grows from 47 % for Ψ_1 to 90 % for Ψ_2, 128 % for Ψ_3, 159 % for Ψ_4 and 182 % for Ψ_5. This sharp widening of the range of variation of primal measures as k rises to 5 reflects their sensitivity to the income shortfalls of people far below the median. This high sensitivity to very low income values, which may often arise from reporting errors, makes the more robust dual measures preferable.

The high correlation between the primal and dual measures, as regards both their values and the implied country ordering, indicates that we could narrow down our attention to only one of them. The relative poverty gap $\Psi_1 = \Pi_1$ is informative about how much, on average, incomes below the median fall short of the median itself, but it has the drawback of being indifferent to the way such incomes are distributed (as shown in Figure 9.2 by its marginal valuation of income always equal to 1). This suggests that we should consider measures characterised by values of k greater than 1. On the other hand, dual measures seem to be preferable for their greater robustness. In particular, the dual measure has some attractive features. First, it is sensitive to income distribution below the median but might be considered to not overstress the depth of poverty, using a relatively low value of k. Second, it is a function of the conditional Gini coefficient, whose metric is well known in inequality studies. Third, besides Aaberge and Atkinson's (2013) theoretical justification, it has also solid

Table 9.1: AROP rate, primal poverty measures and dual poverty measures, EU-27 and United Kingdom, 2018
(%)

Country	AROP rate		$\Psi_1 = \Pi_1$		Ψ_2		Ψ_3		Ψ_4		Ψ_5		Π_2		Π_3		Π_4		Π_5	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
Czechia	9.6	1	12.6	1	4.6	1	2.1	1	1.1	1	0.7	1	17.3	1	20.1	1	22.0	1	23.4	1
Finland	12.0	2	13.7	3	5.3	2	2.5	2	1.3	2	0.8	2	18.7	3	21.4	2	23.3	2	24.6	2
Slovakia	12.2	3	12.6	2	5.4	3	3.0	6	1.9	8	1.4	10	18.3	2	21.8	3	24.3	5	26.1	6
Denmark	12.7	4	14.3	6	6.0	6	3.2	8	2.0	9	1.4	9	19.7	6	22.9	6	25.1	8	26.7	8
Hungary	12.8	5	15.3	11	6.9	13	3.9	14	2.6	15	1.9	16	21.1	12	24.5	13	26.8	13	28.6	14
Netherlands	13.3	6	14.5	7	6.3	9	3.4	10	2.2	11	1.6	11	20.1	7	23.3	9	25.6	9	27.3	10
Slovenia	13.3	7	13.9	4	5.6	4	2.7	3	1.5	3	0.9	3	19.2	5	22.2	5	24.1	4	25.6	4
France	13.4	8	13.9	5	5.6	5	2.7	4	1.5	4	0.9	5	19.2	4	22.1	4	24.1	3	25.5	3
Austria	14.3	9	14.9	9	6.6	10	3.6	12	2.3	12	1.6	12	20.7	10	24.1	11	26.4	12	28.1	12
Poland	14.8	10	15.3	12	6.9	14	3.8	13	2.4	13	1.7	13	21.2	13	24.6	14	26.9	14	28.6	13
Ireland	14.9	11	14.9	8	6.2	7	3.1	7	1.8	6	1.2	7	20.2	8	23.1	8	25.0	7	26.4	7
Cyprus	15.4	12	15.2	10	6.3	8	3.0	5	1.6	5	0.9	4	20.4	9	23.1	7	24.8	6	26.0	5
Germany	15.9	13	15.7	14	7.1	15	3.9	15	2.5	14	1.8	14	21.5	15	24.8	15	27.1	15	28.7	15
Sweden	16.4	14	15.8	16	7.3	16	4.1	16	2.7	16	1.9	17	21.7	16	25.1	16	27.4	16	29.1	16
Belgium	16.4	15	15.7	15	6.9	12	3.6	11	2.1	10	1.4	8	21.3	14	24.3	12	26.3	11	27.7	11
Malta	16.8	16	15.5	13	6.6	11	3.3	9	1.9	7	1.2	6	20.9	11	23.8	10	25.7	10	27.0	9
Portugal	17.3	17	16.3	17	7.6	17	4.3	17	2.7	17	1.8	15	22.4	17	25.8	17	28.0	17	29.7	17
Luxembourg	18.3	18	17.4	18	8.7	18	5.3	20	3.7	22	2.8	23	23.8	18	27.5	18	30.0	19	31.9	20
Greece	18.5	19	17.6	21	8.9	21	5.4	22	3.7	20	2.8	20	24.1	21	27.8	22	30.3	22	32.2	22
United Kingdom	18.8	20	17.5	20	8.8	19	5.3	21	3.7	21	2.8	22	23.9	19	27.6	19	30.1	20	31.9	21
Croatia	19.3	21	17.4	19	8.8	20	5.2	19	3.5	19	2.5	19	24.0	20	27.7	21	30.1	21	31.8	19
Italy	20.3	22	18.7	23	10.1	25	6.6	27	4.9	27	3.9	27	25.7	25	29.7	25	32.4	27	34.4	27
Spain	21.5	23	18.8	25	10.0	24	6.3	24	4.4	24	3.3	25	25.6	24	29.4	24	31.9	24	33.7	24
Estonia	21.9	24	18.3	22	9.0	22	5.2	18	3.3	18	2.3	18	24.4	22	27.6	20	29.7	18	31.2	18
Bulgaria	22.0	25	18.8	24	9.7	23	5.9	23	3.9	23	2.8	21	25.4	23	29.0	23	31.3	23	32.9	23
Lithuania	22.9	26	19.5	27	10.4	27	6.5	26	4.5	26	3.4	26	26.2	26	29.8	26	32.2	26	33.9	26
Latvia	23.3	27	19.4	26	10.4	26	6.4	25	4.4	25	3.3	24	26.2	27	29.8	27	32.1	25	33.9	25
Romania	23.5	28	20.1	28	11.5	28	7.7	28	5.7	28	4.4	28	27.6	28	31.6	28	34.2	28	36.1	28

Note: The countries are ranked according to their AROP rate.

Reading note: In Czechia, the AROP rate is 9.6 %, the lowest among the EU Member States in 2018. The country also has the smallest primal and dual measures of income poverty, always ranking 1st.

Source: Authors' computations, UDB March 2020.

Table 9.2: Spearman paired correlation coefficients between country ranks based on the AROP rate, the primal poverty measures and the dual poverty measures for selected values of *k*

	AROP rate	$\Psi_1 = \Pi_1$	Ψ_2	Ψ_3	Ψ_4	Ψ_5	Π_2	Π_3	Π_4
$\Psi_1 = \Pi_1$	0.969	–	–	–	–	–	–	–	–
Ψ_2	0.942	0.989	–	–	–	–	–	–	–
Ψ_3	0.891	0.958	0.981	–	–	–	–	–	–
Ψ_4	0.863	0.936	0.966	0.994	–	–	–	–	–
Ψ_5	0.828	0.906	0.944	0.981	0.993	–	–	–	–
Π_2	0.956	0.994	0.995	0.971	0.951	0.924	–	–	–
Π_3	0.933	0.982	0.996	0.986	0.970	0.948	0.993	–	–
Π_4	0.906	0.966	0.987	0.996	0.986	0.969	0.980	0.992	–
Π_5	0.891	0.958	0.981	0.999	0.993	0.980	0.972	0.986	0.997

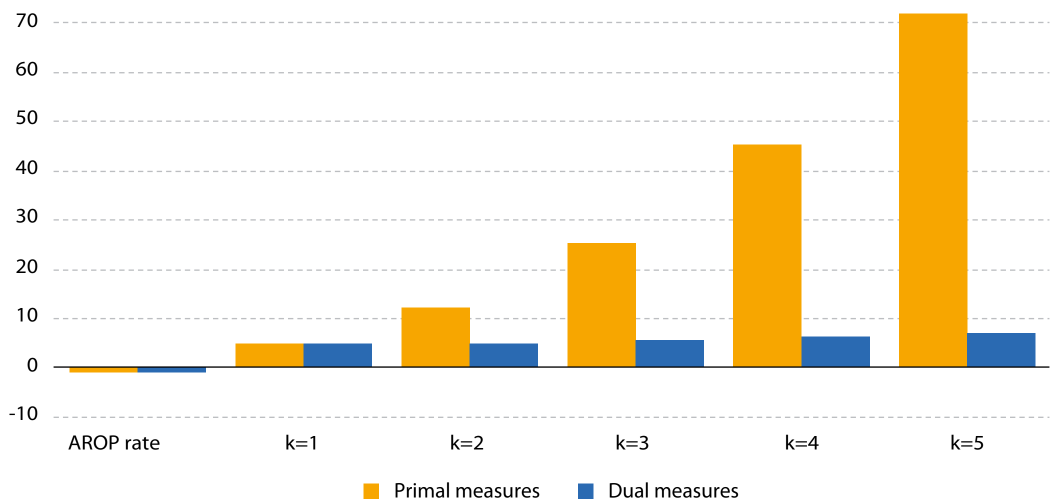
Note: All estimates are statistically significant at 0.001 level.

Reading note: The correlation between the country ranks based on the AROP rate and those based on the poverty measure $\Psi_1 = \Pi_1$ is equal to 0.969.

Source: Authors' computations, UDB March 2020.

Figure 9.3: Poverty differences between the Netherlands and France for selected indices, 2018

(%)



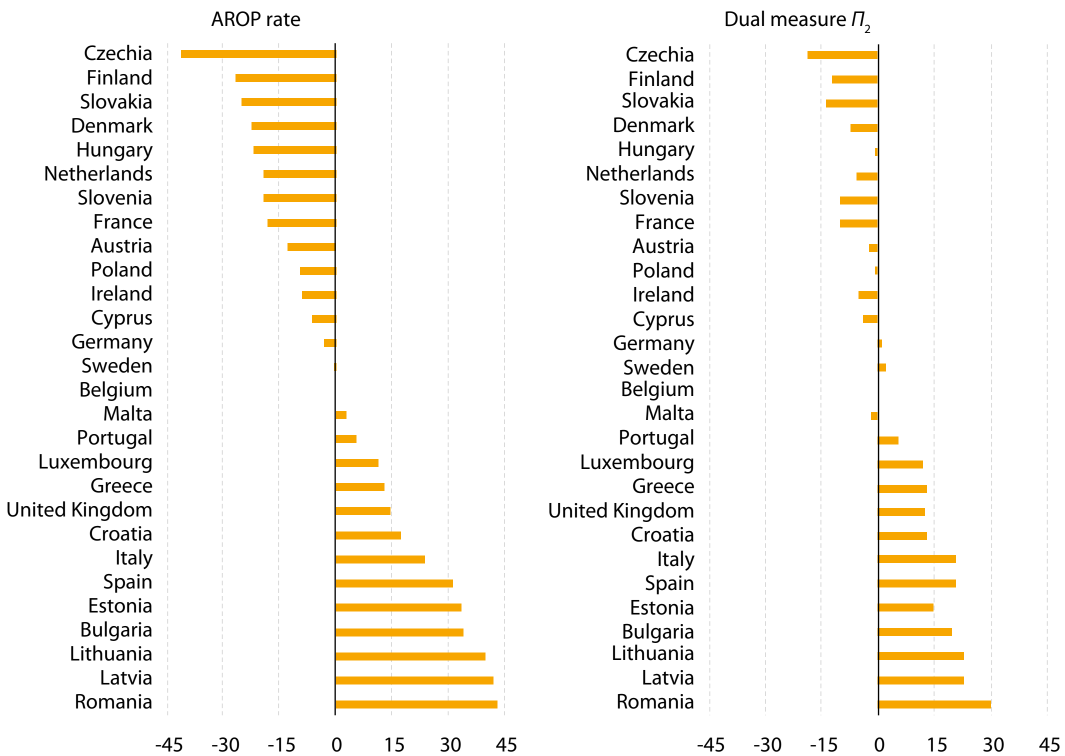
Reading note: In the Netherlands the AROP rate is 1 % lower than in France, but the primal and dual measures are consistently higher by 5 % or more.

Source: Authors' computations, UDB March 2020.

conceptual foundations in the Borda ordering or in 'a "relativist" view of poverty, viewing deprivation as an essentially relative concept... The lower a person is in the welfare scale, the greater his sense of poverty, and his welfare rank among others may be taken to indicate the weight to be placed on his income gap', as argued by Sen long ago (1976, p. 222).

We compare estimates of poverty in the EU countries in 2018 based on the dual measure Π_2 as well as the AROP rate in Figure 9.4, by expressing results as percentage differences from the Belgian value. As discussed, variations in country ordering based on these two measures are generally modest, although changes are noticeable for seven countries: Ireland and Cyprus move up three positions, France four and Malta five, whereas Poland and Italy lose three positions and Hungary moves down seven positions when we change from the AROP rate to Π_2. Despite this re-ranking, the pattern is broadly confirmed, with the highest levels of poverty found in the Baltic States, Bulgaria, Italy, Romania and Spain. Differences across countries shrink, however, when shifting from the AROP rate to Π_2: for instance, measured poverty in Romania remains the highest but falls from 43 % to 30 % of the Belgian values. Considering the whole income distribution below the median has an impact: levels of measured poverty appear to be less diverse across EU nations than the AROP rate suggests.

Figure 9.4: Poverty differences, EU-27 countries and United Kingdom, 2018
(% relative difference with respect to Belgium)



Note: The countries are ranked according to the AROP rate.

Reading note: In Czechia the AROP rate is 42 % lower than in Belgium, while the dual measure is only 19 % lower. Belgium is taken as reference because of its median value.

Source: Authors' computations, UDB March 2020.

Our results highlight, first, that considering the entire distribution (below the poverty threshold) matters for poverty evaluation and, second, that any conclusion on how much the poverty level in one country exceeds that in another country depends heavily on the choice of the poverty index. These aspects are far from new, but represent critical factors in the monitoring of poverty from a policy perspective. The selection of the index equally matters for deriving the optimal allocation of anti-poverty budgets, the question to which we turn in the next section.

9.5. The dependence of optimal allocations of anti-poverty budgets on the choice of the poverty measure

The implications for the optimal allocation of an anti-poverty budget of adopting a certain poverty index are usually overlooked, although they should be of some concern when the index is turned into a policy target. In the abstract, all other things being equal, the aggregate amount of income necessary to eliminate poverty is the sum of all poor individuals' income shortfalls calculated with respect to the poverty line. This amount S is given by

$$S = \sum_{\{i: y_i < z_i\}} (z_i - y_i) v_i = \sum_{\{i: x_i < z\}} (z - x_i) e_i v_i, \quad (9.9)$$

where $z_i = ze_i$ is household i's specific poverty line, $y_i = x_i e_i$ its actual (non-equivalised) income and v_i its (normalised) weight. The poverty line faced by household i is obtained by multiplying the poverty line z for the reference household by the number of equivalent adults e_i. The aggregate poverty gap is the ratio of S to total household income, and is itself a summary poverty measure accounting for both the spreading and the severity of poverty. Clearly, the aggregate poverty gap must be understood as the outcome of a statistical measurement exercise and not of a fully fledged tax–benefit microsimulation. An actual monetary transfer raising all incomes to the level of the poverty threshold would affect individuals' economic decisions (consumption and saving, labour supply, etc.), of the poor as well as the non-poor to the extent that they are called to contribute to the financing of the transfer, with sizeable macroeconomic effects. The resources needed to eradicate income poverty would differ from S as defined in equation (9.9) if we were to account for all individual and macroeconomic responses.

Figure 9.5 shows for all EU countries the aggregate poverty gap in 2018, or the proportion of total household income that is necessary to eliminate poverty. Its value depends on the poverty line, which is set at 60 % of the median for the AROP rate and at the median itself for the primal and dual poverty measures, as the latter embody the idea that any income value below the median could be an acceptable threshold. The resources necessary to eliminate poverty are understandably much smaller for the AROP rate than for the primal and dual measures.

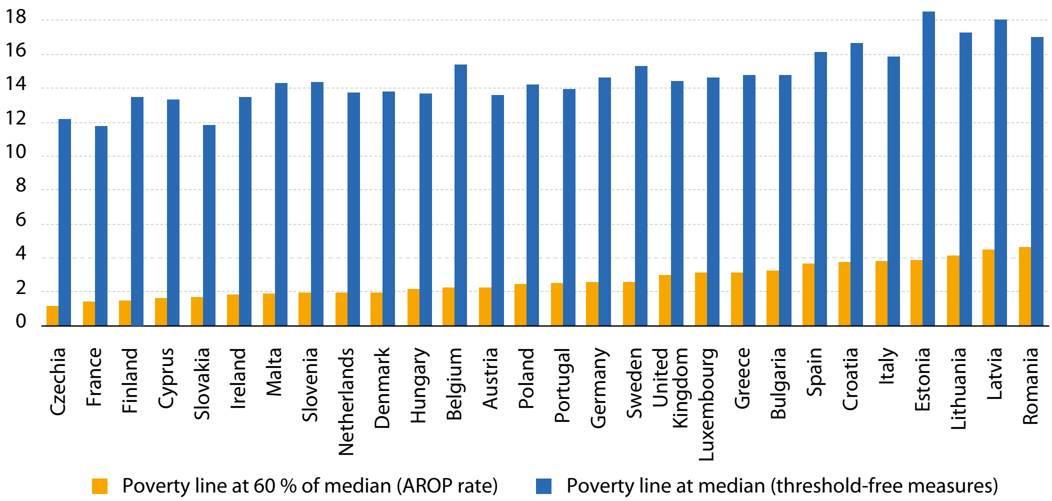
The aggregate poverty gap varies substantially across the EU. With either level of poverty line, it is highly correlated with the AROP rate, being lower in countries where the AROP rate is low and higher in those where it is high. For example, Czechia, France and Slovakia, whose AROP rates are among the lowest, would need around 12 % of total household income to move everyone below it to the country-specific median income. At the other extreme, the three Baltic States and Romania would need 17–18 % of their total household income to reach the same result. Much less would be required to bring the AROP rate down to zero: a budget for anti-poverty policies of 4 % of total household income would be more than sufficient in most countries.

To assess the distributional consequences of alternative allocations of an anti-poverty budget, we imagine that each country assigns to this budget 1 % of the country's total household (non-equivalised) disposable income. The amount transferred to the individuals living in poverty is determined in such a way as to maximise the reduction of the target poverty index. As mentioned, any allocation of the budget is optimal for the relative poverty gap $\Psi_1 = \Pi_1$, while all primal and dual poverty measures with $k > 1$ are distributionally sensitive and lead to p-type policies. These policies rank all poor individuals by income level and then raise the incomes of the poorest to the maximum possible level given the budget. In practice, this implies lifting the income of the poorest one by one: the first transfer brings the poorest individual's income to the income level of the second poorest; the next transfers lift the incomes of these two individuals to the level of income of the third poorest, and so on. On the contrary, the head count AROP rate brings to adopt an r-type policy, which implies allocating the budget to the richest among the poor first. It should be borne in mind that this is a conceptual exercise in which transfers ought to be seen as a sort of pure gift with no impact on any other variable (tax liabilities, labour supply, etc.). We simply consider the direct effect of this abstract transfer policy and ignore the indirect effects that might arise. We are also implicitly overlooking any practical problems that would be encountered in the implementation of the policy and assuming perfect targeting.

As Figure 9.5 shows, a budget equal to 1 % of total household (non-equivalised) disposable income is insufficient to eradicate poverty as measured by the AROP rate even in Czechia. It is all the more true when the target poverty index is a primal or dual measure. Table 9.3 reports for each country the percentage decrease in measured poverty in 2018 after optimally allocating the 1 % anti-poverty budget according to each selected index. On average, the AROP rate falls by two thirds; its reduction ranges from 49 % in Romania to 97 % in Czechia, and is inversely related to the poverty level. The corresponding reduction is smaller if the target index is a primal or dual measure, with substantial variation due to the degree of distribution sensitivity. The relative poverty gap exhibits the smallest drops in income poverty, between 5 % and 9 %. As *k* increases, measured poverty goes down more intensely. This is not surprising. For any $k > 1$,the allocation of the anti-poverty budget does not change, but measured poverty does, since higher values of *k* imply assigning higher weights to the poor people whose incomes are far below the median, and smaller weights to those who stand close to the median. With a very large *k*, individuals with

Figure 9.5: Aggregate poverty gap for alternative poverty lines, EU-27 countries and United Kingdom, 2018

(%)



Note: The countries are ranked according to the aggregate poverty rate corresponding to the AROP indicator.

Reading note: In Czechia policymakers would need slightly more than 1 % of total household income to eradicate poverty, taking the AROP rate as a target; they would need 12 %, taking instead any of the primal and dual measures.

Source: Authors' computations, UDB March 2020.

small income shortfall contribute virtually nothing to the poverty index, as they have a negligible weight; besides, they receive a tiny transfer, if any. Thus, after optimally allocating a budget equal to 1 % of total household income, measured poverty falls in Czechia by 24 % with Ψ_2, 43 % with Ψ_3, 61 % with Ψ_4 and 76 % with Ψ_5. The dispersion of these values reflects only the different weighting structure embodied in the indices and not the allocation of the budget, which is the same for all of them. Apart from this difference in size, the cross-country pattern of poverty declines is similar among indices with diverse *k*. The same holds for dual poverty measures, although they signal substantially lower poverty reductions than primal indices with equal distributional sensitivity. For instance, poverty decreases by 8 % to 12 % with Π_2 relative to 15 % to 26 % with Ψ_2. This can be seen as another example of the greater robustness of dual measures.

The figures in Table 9.3 illustrate the extent to which the measured progress in poverty reduction depends on the choice of the poverty index. The greater progress found for the AROP rate follows from two factors. First, it relies on a poverty threshold that is substantially lower than the one underlying the primal and dual measures (the median), although those measures assign very low weights to people close to the threshold for sufficiently high values of *k*. Second, it prioritises the richest among the poor in the allocation of the anti-poverty budget, which is the opposite of what happens with the primal and dual measures.

To figure out what this disturbing feature of the AROP rate implies, in Table 9.4 we compare the mean equivalised income of all AROP individuals before and after the distribution of the 1 % budget. (The means are expressed as percentage ratios to the poverty line fixed at 60 % of the median, whose value is not affected by the anti-poverty policy.) In Romania the allocation of the 1 % budget informed by the AROP rate (r-type policy) would allow a considerable reduction in the AROP rate itself, from 23.5 % to 12.1 %. The share of individuals who, after the transfer, would be left with income below the poverty line would still be sizeable, but their mean income would not: just 39 % of the poverty line, compared with the 61 % calculated before the transfer for the larger pool of all AROP individuals. If the anti-poverty budget were instead allocated according to any of the threshold-free measures with $k > 1$ (p-type policy), the share of the AROP individuals would not change, as the available resources would bring everybody closer to the poverty line but would not be sufficient for someone to cross it; their mean income, however, would rise to 69 % of the poverty line, or 14 % more than its pre-allocation value.

The change in the (cumulative) distribution of income with the two policies is shown in Figure 9.6. With the r-policy targeting the AROP rate, income would not change and would remain below 40 % of the median for the bottom 12.1 % of the population, while it would rise to the poverty threshold for the next 11.4 %, which is the richer group of the pre-allocation poor individuals (middle panel). With the p-policy targeting any of the threshold-free measures with $k > 1$,the anti-poverty resources would be used to raise the income of the poorest 9 % of the population to a minimum income level of almost a third of the median (right panel). While the post-allocation distributions obviously dominate the original distribution, they cross and cannot be ordered unless we impose further restrictions on social preferences.

On average across all 28 countries, with the r-type policy the AROP rate drops substantially, from 17 % to 5 %, but the mean income of the AROP individuals also diminishes, from 72 % to 41 % of the poverty line. These results are not surprising, since in most European countries half of the poor have income shortfalls less than 30 % from the poverty line, and only a small fraction have income deficits exceeding 80 % (Kyzyma, 2020). Conversely, with the p-type policy the AROP rate is unaffected, but the mean income of the AROP individuals rises by a sixth to 83 % of the poverty line. There is considerable variation around these averages, with progress being larger in countries starting from lower AROP rates. However, the meaning of 'progress' is notably different between the two types of policies: it means lower AROP rates for the r-type policy, but higher mean incomes of the AROP individuals for the p-type policy. These policy choices have a cost too: the r-type policy is bound to leave behind the poorest among the poor; the p-policy is incapable of lifting anybody above the poverty line. Which policy type is preferable from a normative point of view is an open issue.

Table 9.3: Poverty reduction with an optimal anti-poverty budget of 1 % of the national total household income for selected poverty measures, EU-27 countries and United Kingdom, 2018
(%)

Country	AROP rate	$\Psi_1 = \Pi_1$	Ψ_2	Ψ_3	Ψ_4	Ψ_5	Π_2	Π_3	Π_4	Π_5
Czechia	96.5	8.4	23.9	42.8	60.9	75.5	11.6	14.4	16.8	18.9
Finland	89.7	6.8	19.4	35.5	52.3	67.3	9.6	12.0	14.2	16.1
Slovakia	86.7	8.8	26.3	46.6	64.5	77.8	11.7	14.2	16.4	18.4
Denmark	79.8	7.1	21.2	39.3	57.3	72.3	9.8	12.3	14.4	16.3
Hungary	75.3	7.3	21.9	40.1	57.7	71.9	10.2	12.7	14.9	16.9
Netherlands	82.2	7.4	22.2	41.3	59.8	74.6	10.3	12.8	15.1	17.1
Slovenia	78.3	6.3	17.9	32.2	46.7	59.8	8.8	10.9	12.8	14.4
France	90.3	8.6	23.2	40.3	56.9	71.0	11.7	14.4	16.7	18.8
Austria	75.6	7.0	20.6	37.6	54.5	69.0	9.7	12.1	14.1	16.0
Poland	71.9	6.8	19.8	36.1	52.5	66.7	9.4	11.7	13.7	15.5
Ireland	84.5	6.8	19.3	35.5	52.7	68.2	9.5	12.0	14.1	16.1
Cyprus	82.5	7.5	19.3	33.1	47.1	60.1	10.4	12.8	14.9	16.8
Germany	69.8	6.5	18.9	35.0	51.7	66.5	9.1	11.3	13.4	15.2
Sweden	72.1	6.5	19.1	35.7	52.9	67.9	9.0	11.3	13.4	15.3
Belgium	73.5	6.7	18.6	33.8	50.0	64.9	9.4	11.8	13.9	15.7
Malta	79.1	7.2	19.3	34.2	49.8	64.1	10.1	12.5	14.7	16.6
Portugal	69.6	7.1	19.9	35.3	50.7	64.3	9.9	12.3	14.4	16.2
Luxembourg	67.5	6.3	18.7	34.6	50.7	64.7	8.9	11.1	13.1	14.9
Greece	61.5	6.9	19.5	34.9	50.2	63.6	9.6	11.9	13.9	15.7
United Kingdom	66.1	7.2	20.6	37.3	53.9	67.9	10.1	12.6	14.8	16.7
Croatia	55.4	5.9	16.4	29.4	42.9	55.6	8.1	10.0	11.8	13.3
Italy	59.1	6.4	18.4	33.3	48.3	61.4	8.9	11.0	12.9	14.6
Spain	58.5	6.4	17.9	32.2	46.8	60.0	9.0	11.2	13.1	14.9
Estonia	55.0	5.3	15.0	27.9	42.3	56.4	7.6	9.7	11.6	13.3
Bulgaria	57.1	7.6	20.0	34.5	48.8	61.4	10.5	13.0	15.2	17.0
Lithuania	53.7	5.9	16.4	29.9	44.0	57.2	8.3	10.5	12.4	14.0
Latvia	51.1	5.4	15.2	27.7	41.1	54.0	7.7	9.7	11.5	13.1
Romania	48.5	6.1	16.6	29.2	42.1	53.9	8.4	10.4	12.2	13.7

Note: The countries are ranked according to their AROP rate.

Reading note: In Czechia the AROP rate falls by 96.5 % after allocating among the poor a budget equal to 1 % of the Czech total household income in such a way as to maximise the reduction in the AROP rate; it declines by 11.6 % when the allocation is based on Π_2.

Source: Authors' computations, UDB March 2020.

Table 9.4: AROP rate and relative mean income of poor people before and after optimally allocating an anti-poverty budget equal to 1 % of the country's total household income, EU-27 countries and United Kingdom, 2018
(%)

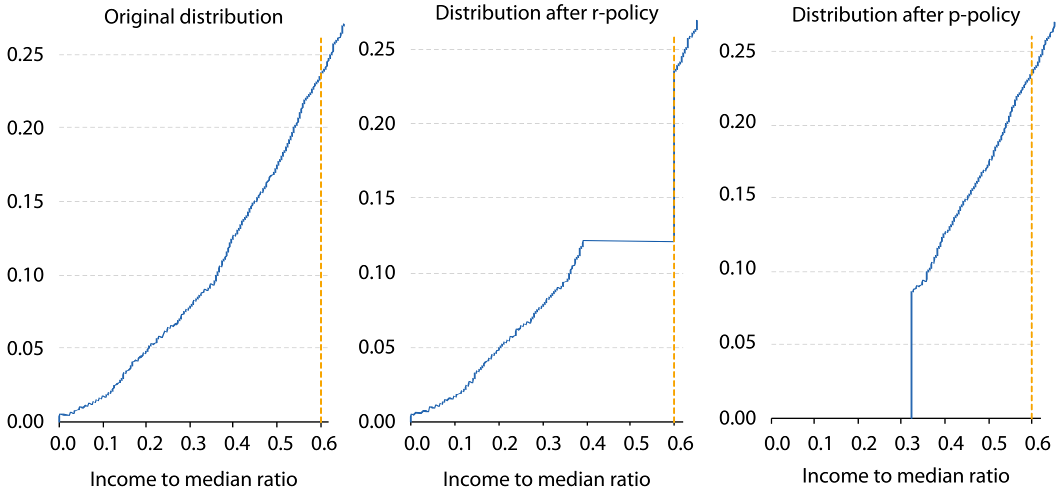
Country	AROP rate (%)		Mean income of AROP poor (% of AROP line)		
				Post-allocation	
	Pre-allocation	Post-allocation	Pre-allocation	AROP rate allocation	$\Psi_k, \Pi_k > 1$ allocation
Czechia	9.6	0.3	79.3	20.7	97.6
Finland	12.0	1.2	80.4	39.8	93.4
Slovakia	12.2	1.6	74.3	22.5	89.4
Denmark	12.7	2.6	74.0	37.2	87.2
Hungary	12.8	3.2	68.3	30.0	82.9
Netherlands	13.3	2.4	73.7	27.2	87.1
Slovenia	13.3	2.9	78.1	51.9	89.2
France	13.4	1.3	78.9	38.6	93.7
Austria	14.3	3.5	72.2	38.0	84.4
Poland	14.8	4.2	71.6	41.1	83.2
Ireland	14.9	2.3	78.8	41.4	90.0
Cyprus	15.4	2.7	79.8	56.7	92.1
Germany	15.9	4.8	72.7	45.6	83.4
Sweden	16.4	4.6	72.9	40.8	83.2
Belgium	16.4	4.3	76.5	50.9	87.1
Malta	16.8	3.5	78.9	51.6	90.0
Portugal	17.3	5.2	71.6	43.8	82.9
Luxembourg	18.3	5.9	67.4	34.4	77.4
Greece	18.5	7.1	66.1	39.9	77.0
United Kingdom	18.8	6.4	68.0	37.1	79.2
Croatia	19.3	8.6	67.2	46.4	76.0
Italy	20.3	8.3	63.1	33.3	72.9
Spain	21.5	8.9	65.8	40.1	75.2
Estonia	21.9	9.8	72.5	54.0	79.8
Bulgaria	22.0	9.4	67.4	44.9	78.2
Lithuania	22.9	10.6	66.6	44.5	74.9
Latvia	23.3	11.4	66.7	46.9	74.2
Romania	23.5	12.1	60.6	38.9	69.3

Note: The countries are ranked according to their (pre-transfer) AROP rate.

Reading note: In Czechia the AROP rate falls from 9.6 % to 0.3 % after allocating among the poor a budget equal to 1 % of the country's total household income in such a way as to maximise the reduction in the AROP rate; the mean equivalised income of the AROP poor correspondingly changes from 79.3 % to 20.7 % of the AROP line (or 60 % of the median income); the mean equivalised income of the post-allocation AROP poor instead rises to 97.6 % of the AROP line if the allocation is based on a primal or dual measure with $k > 1$.

Source: Authors' computations, UDB March 2020.

Figure 9.6: **Income cumulative distribution function before and after optimally allocating an anti-poverty budget equal to 1 % of the country's total household income in Romania, 2018**



Reading note: The left panel shows the original cumulative distribution of household incomes in Romania up to around the poverty line (the dashed vertical line at 0.6): for instance, the poorest 10 % of Romanians has income lower than 37 % of the median; the next panels show the distributions obtained after allocating the anti-poverty budget taking as a target either the AROP rate (middle panel) or any primal or dual measure with $k > 1$ (right panel).

Source: Authors' computations, UDB March 2020.

9.6. Conclusion

In this chapter, we have examined poverty evaluation in the EU by focusing on two critical features of head count measures: the arbitrariness of the choice of the poverty threshold and the insensitivity to the seriousness of the poverty condition. We have compared empirical results for the AROP rate, a constituent of the official EU poverty target, with those for 10 (in fact, 9, as the primal and dual measures coincide for $k = 1$) alternative indices belonging to a class of threshold-free distributionally sensitive measures characterised by Aaberge and Atkinson (2013). We have reported estimates for all the 28 Member States in 2018 based on EU-SILC data.

Our main findings can be summarised as follows. First, the correlation of country rankings based on the different selected measures is high and statistically significant, although movements by one to three positions up or down are frequent. The rankings are more robust for dual than for primal measures. Second, accounting for income distribution below the poverty threshold impinges on the evaluation of poverty levels: the extent to which measured poverty is higher in one country than in another depends heavily on the choice of the poverty index. Third, the optimal allocation of an anti-poverty budget may change considerably if a different poverty index is chosen as a target, revealing their ethical views underlying the choice. With an index leading to an r-type policy, such as the AROP rate, social progress is achieved by lifting as many people as possible above the poverty line, regardless of the condition of those who are left below it. With an index leading to a p-type policy, such as Π_2, social progress is pursued by improving the condition of the poorest among the poor, although the number of poor people need not fall. While these aspects are mostly known, they need to be closely scrutinised when the monitoring of poverty is part of a policy process.

Long ago, Watts famously remarked that a poverty head count measure has 'little but its simplicity to recommend it' (1968, p. 326). On the other hand, Atkinson argued that 'a minimum income may be seen as a basic right, in which case the head-count may be quite acceptable as a measure of the number deprived of that right' (1987, p. 755). In fact, simplicity and the basic right justification are appealing features for a policy target. Yet the insensitivity to the severity of deprivation and the disturbing implications for the optimal allocation of the resources earmarked to poverty alleviation are critical weaknesses of head count indices. The threshold-free distributionally sensitive measures analysed in this chapter may provide a valuable complement. The high correlation across measures differing only for *k*, the parameter capturing the aversion to poverty depth, suggests that we could tentatively converge on a single value of *k*. Relatively high values of *k* can be discarded because they imply an attention unbalanced towards extreme poverty conditions. On the other hand, the relative poverty gap, corresponding to $k = 1$, has the shortcoming of being indifferent to how incomes are distributed below the median, hence providing no hint on the optimal allocation of an anti-poverty budget. Dual measures seem to be preferable for their greater robustness. In the light of these observations, as discussed in the chapter, there are good reasons to consider supplementing the AROP rate with the dual measure Π_2, which embodies the conditional Gini coefficient.

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Understanding inequalities in health and housing conditions

10 Comparing unmet need for medical care across EU countries: does risk adjustment matter?

Valerie Moran, Andrea Riganti, Luigi Siciliani and Andrew M. Jones ([11])

10.1. Introduction

Under various international agreements, EU governments have an obligation to ensure equitable access to core health services, which implies a commitment to address levels of unmet need for medical care (EXPH, 2016). In 2017, the European Commission put forward the European Pillar of Social Rights to deliver a social and fair Europe and to serve as a compass for change. The pillar includes three main dimensions in the field of employment and social policies. The third dimension covers social protection and inclusion, including access to healthcare. The pillar is accompanied by a 'social scoreboard', which monitors its implementation by tracking trends and performances across EU countries and feeds into the European Semester of economic policy coordination. The European Semester supports Member States to coordinate their economic policies and deal with their economic challenges (European Commission, 2017).

A common issue facing European countries is the unequal distribution of access to healthcare and subsequent inequalities in health outcomes (EXPH, 2017). An indicator currently used in the social scoreboard to measure access to healthcare is self-reported unmet need for medical care, which draws on data from EU-SILC. Countries with higher levels of unmet need will face more challenges in improving access to healthcare.

When undertaking comparisons of health outcomes across providers or health systems, it is common to adjust measures for influential risk factors outside the direct control of healthcare providers or health systems, to attempt to facilitate comparisons (Iezzoni, 2009; Moger and Peltola, 2014). Risk adjustment variables can encompass demographic and socioeconomic factors (Iezzoni, 2009; Juhnke et al., 2016; OECD, 2019). Access to healthcare is also affected by public policy outside the health sector, such as education, employment and social protection (EXPH, 2016).

Comparisons of unmet medical need across EU countries using EU-SILC data are not adjusted for individual-level risk factors. Indeed, measuring unadjusted unmet need for medical care allows countries to assess the extent to which access to medical care is an important societal problem that national governments should address, and to monitor how unmet need develops over time. The unmet need indicator could be complemented by an adjusted measure of unmet need for medical care, which recognises that countries differ in factors that influence unmet need and are outside the control of the health system. Adjusting for demographic and socioeconomic factors makes differences in unmet need more comparable across countries when the aim is the assessment of health

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It is important to acknowledge the subjective nature of self-reported unmet need, which may be influenced by factors that are unobserved and cannot be easily controlled. Such factors include cultural norms and attitudes towards health and illness, health knowledge or literacy, and expectations of health services (Chaupain-Guillot and Guillot, 2015; Israel, 2016; Eurostat, 2010; Baeten et al., 2018). For example, respondents with low health knowledge or literacy may under-report unmet need (Chaupain-Guillot and Guillot, 2015). These factors are likely to vary across countries, and this should be borne in mind when comparing the indicator across countries.

Previous studies have used EU-SILC data to investigate individual- and country-level determinants of self-reported unmet medical need across countries (Chaupain-Guillot and Guillot, 2015; Elstad, 2016; Detollenaere et al., 2017; Reeves et al., 2017; Israel, 2016; Fiorillo, 2019; Madureira-Lima et al., 2018). However, these studies do not compare differences in unmet need for medical care across countries before and after adjusting for individual-level variables, which is our focus. By undertaking this exercice, we provide insights into how unadjusted differences in unmet need across countries are sensitive to the inclusion of risk factors, and the reliability of current performance comparison in unmet need across the EU.

In this chapter, we investigate how much unmet need differs across EU countries before and after adjusting for demographics (age and gender), possible determinants of need (chronic conditions) and socioeconomic status (education, unemployment, AROP and household disposable income). We provide confidence intervals for unmet need in each country to show the extent to which differences across countries are statistically significant.

This chapter proceeds as follows: Section 10.2 describes the EU-SILC data used in our analysis; Section 10.3 explains our risk adjustment method; Section 10.4 presents the results; Section 10.5 discusses our findings, gives policy recommendations and concludes.

10.2. Data

EU-SILC measures unmet need during the previous 12 months for (1) medical examination or treatment and (2) dental examination or treatment. We focus only on unmet need for medical examination or treatment, as public coverage for dental care is more limited across EU countries (OECD and EU, 2020) and accounting for these differences is beyond the scope of this study.

The dependent variable, unmet need, measures if the individual (aged 16 and over) experienced unmet need for medical examination or treatment during the previous 12 months. More precisely, unmet need is a dichotomous variable with two possible outcomes: (1) yes, there was at least one occasion when the person really needed an examination or treatment but did not receive it; and (2) no, there was no occasion when the person really needed an examination or treatment but did not receive it. In Appendix 10.1 we provide further detail on the unmet need question in EU-SILC.

In some countries, adult variables are obtained by means of interview from a sample of persons using the selected respondent model (i.e. collecting the personal interview for a representative sample composed of one adult aged 16 years or over per household; see Chapter 2 of this volume).

The UDB includes 608 180 observations, of which 513 204 are considered adults (aged 16 years or over) in 2018, with household-level income variables observed for 2017 apart from Ireland (calculation on the basis of a moving income reference period) and the United Kingdom (total annual household income calculated on the basis of current income). For Ireland, Slovakia and the United Kingdom, 2018 data were unavailable at the time of analysis, so we used data for 2017.

Covariates include gender, age, chronic illness or condition, education, unemployment status, AROP and income. We include quadratic and cubic functions of age to capture non-linearity in the relationship between unmet need and age. We include a variable to reflect whether or not a respondent suffers from any chronic (long-standing) illness or condition, as countries may differ in terms of population health status and prevention policies. The inclusion of this variable also attempts to capture need for healthcare. In a sensitivity analysis, we consider two additional health variables in EU-SILC: self-reported general health and limitation in activities because of health problems. Self-reported general health is related to how a person perceives their health in general, and all current household members aged 16 and over (or selected respondents) are asked this question. There are five possible answers for this question, which range from very bad to very good. Limitation in activities because of health problems refer to any limitation in activities people usually do because of health problems for at least the past 6 months. This variable has three categories: strongly limited, limited and not limited. We entered the variable into the models using these three categories (as dummy variables) without transformation. Like the other health variables, all household members (or selected respondents) aged 16 or over are asked this question.

Educated people may articulate their needs better or demand more care in the form of self-reported need. Education variables are based on the International Standard Classification of Education (ISCED) 2011 classification (UNESCO and UNESCO Institute for Statistics, 2012). Following previous studies (Börsch-Supan. et al., 2005; Siciliani and Verzulli, 2009), we construct three categorical variables to capture different educational levels. Low education includes categories 0 (no education), 1 (primary education) and 2 (lower secondary education). Intermediate education includes categories 3 (upper secondary education) and 4 (post-secondary, non-tertiary education). High education includes tertiary education categories, from 5 (short-cycle tertiary education) to 8 (doctoral or equivalent level).

The risk of poverty follows the EU definition. We also control for unemployment using the EU-SILC variable used to assess the number of months spent in unemployment in an income reference period. We divide this variable into four levels to capture different durations of unemployment: (1) 0 months in unemployment, (2) between 1 and 6 months in unemployment, (3) between 6 and 11 months in unemployment and (4) 12 months in unemployment.

Individuals with high annual disposable incomes (see Chapter 2 for detailed information on income measurement) have access to a higher level of resources to purchase healthcare (e.g. from the private sector) or to afford higher levels of co-payments. Total annual disposable income is a continuous variable and it is measured in euro. For countries that do not belong to the euro area (namely Bulgaria, Croatia, Czechia, Denmark, Hungary, Poland, Romania, Sweden and the United Kingdom) the conversion factor is provided by Eurostat as a variable in the EU-SILC data set. To adjust for household size, we use the household equivalised income (see Chapter 2 for more details). Moreover, we use the Eurostat deflator (Eurostat, 2020) to adjust income for PPS in order to make comparisons across countries.

In order to analyse the relationship between unmet need and income, we categorise annual equivalised disposable income (expressed in PPS) into deciles based on the distribution across the whole EU sample. As a sensitivity analysis, we consider annual equivalised disposable income in PPS measured as a continuous variable.

Among the initial sample of individuals aged 16 or over (513 204 observations), 27 572 individuals (5.4 %) were excluded because they had missing values on unmet need or were not the selected respondent (in Denmark, the Netherlands, Slovenia, Finland and Sweden), totalling 43 185 observations, 8.4 %. The United Kingdom had the largest percentage (17 %) of missing data on unmet need. Moreover, we excluded from the sample 2 155 observations (0.4 %) because of missing data on covariates (education, n = 1 253; chronic conditions, n = 817; unemployment status, n = 34) and extreme or negative annual equivalised disposable income (under –20 000 PPS, n = 42; over 600 000 PPS, n = 9). The final sample has 440 292 observations.

10.3. Methods

We estimate the following logit model:

$$P\ (y_{ij}|x_{ij}) = F\big(\alpha_j + \textstyle\sum_k \beta^k x_{ij}^k\big),$$

where *yij* is a dummy variable for reporting unmet for individual *i* in country *j* ($j = 1,\ldots,28$); *aj* is a vector of country fixed effects; x_{ij}^{k} is a vector of *k* control variables for individual *i* in country *j*; and $F(z) = e^z / (1 + e^z)$ is the cumulative logistic distribution.

To compare across models with different sets of covariates, for each country we evaluate the predicted probability $\hat{P}_j = F\left(\hat{\alpha}_j + \sum_k \hat{\beta}^k \bar{x}^k\right)$ of reporting unmet need at the EU sample mean of covariates $\bar{x}^k$.

We use personal cross-sectional weights (UDB variable RB050) to ensure the results are representative of population composition. The model is estimated with robust standard errors using Stata Version 16 (StataCorp, 2019) ([137]). We report fixed effects coefficients, which have a log-odds ratio interpretation.

10.4. Results

10.4.1. Descriptive statistics

Table 10.1 shows the descriptive statistics of individuals in our sample. Across the whole EU, 3.2 % of individuals report unmet need. A total of 52.2 % are women. The mean age is 49.1 years. Their education levels are low for 29.1 %, intermediate for 43.4 % and high for 27.4 %. Some 33.7 % of individuals have a chronic condition. The average annual equivalised disposable income is 19 400 PPS. Seventeen per cent are AROP. As many as 91.8 % of individuals are employed or economically inactive, while 4.4 % have been unemployed for 12 months. Compared with individuals in the whole sample, those who report unmet need are more likely to be female, have low education, suffer from a chronic condition, be AROP, be unemployed for 12 months and have a lower average annual equivalised disposable income (mean 13 300 PPS). The mean age of those who report unmet need, 52 years, is a little higher than that of the general population.

([137]) The analysis does not use the methodology developed in the context of Net-SILC2, which is now also used at EU level; see Tim Goedemé's web page on standard errors (https://timgoedeme.com/eu-silc-standard-errors/).

10.4.2. Regression results

Table 10.2 provides the results of the logit models, with the probability of reporting unmet need evaluated at the average EU value of covariates. Column I shows the unadjusted country fixed effects, which represent the (unadjusted) proportion of unmet need for the population. Differences in unmet need across countries are statistically significant at 0.1 % level (*p*-value < 0.001), and 95 % confidence intervals for the country fixed effects are 2 p.p.

Figure 10.1 plots the confidence intervals for each country and shows the extent to which unadjusted unmet need differs across countries. Whereas Luxembourg and Netherlands do not differ in unmet need from each other, they have less unmet need than Belgium or Italy. In Figure 10.1 we also compare unmet need between the unadjusted model and the most comprehensive model, column VI in Table 10.2. We can see that adjusting for several factors (age, gender, chronic condition, education, AROP, unemployment and income) generally reduces differences of unmet need across countries, with income playing a key role. Statistically significant differences in adjusted unmet need remain for the majority of countries. The difference between unadjusted and adjusted unmet need is less than 2 p.p. in 22 countries, and these differences are statistically significant at 5 % level for 9 of these countries. The reduction in unmet need is highest in Estonia (6 p.p.) and Latvia (4 p.p.) and smaller (2–3 p.p.) in Romania, Hungary, Poland and Greece. These differences are all statistically significant at 5 % level.

Next, we describe the contribution of each group of control variables in more detail. Column II in Table 10.2 controls for age and gender and shows that differences in unmet need change by a very small amount after controlling for these variables. This is also illustrated in Figure 10.2, where unadjusted unmet need is compared with unmet need adjusted for demographics, illustrated by the blue dots.

Column III in Table 10.2 controls for chronic conditions and is also illustrated by the red dots in Figure 10.2. The results show that unmet need is reduced relative to column II with the addition of this variable. The reduction is largest in Estonia (3.3 p.p.

Table 10.1: Descriptive statistics for general population and respondents reporting unmet need, EU-27 and United Kingdom, 2018

Variable	Mean, general population	SD, general population	Mean, among those with unmet need	SD, among those with unmet need
Unmet need (%)	3.2	-		-
Gender: female (%)	52.2	-	56.1	-
Education: high (%)	27.4	-	20.8	-
Education: intermediate (%)	43.4	-	42.7	-
Education: low (%)	29.1	-	36.5	-
Chronic conditions: yes (%)	33.7	-	55.2	-
AROP: yes (%)	17.0	-	28.0	-
Unemployment: 0 months (%)	91.8	-	88.2	-
Unemployment: 1–6 months (%)	2.4	-	3.2	-
Unemployment: 7–11 months (%)	1.3	-	1.7	-
Unemployment: 12 months (%)	4.4	-	6.9	-
Age (years)	49.1	18.1	52.0	17.4
Income (disposable), 1 000 PPS	19.4	14.7	13.3	10.5

Note: SD, standard deviation.

Reading note: Mean values refer to individuals in our sample.

Source: Authors' computations, UDB September 2019.

reduction, from 18.3 % to 15.0 %), followed by Latvia, Poland, Finland and the United Kingdom (1.1–1.5 p.p. reduction). There are, however, exceptions: unmet need increases in Greece, Italy and Romania as the lower national prevalence of chronic conditions is substituted with the higher EU average prevalence.

Column IV in Table 10.2 controls for education and is also illustrated by the light green dots in Figure 10.2. There is a negligible change in unmet need in all countries (variation is 0.3 p.p. or less) relative to column III, except for Latvia, Estonia, Portugal and Greece, where it is more pronounced. Unmet need increases in Latvia and Estonia (by 0.4 p.p. and 0.7 p.p. respectively), where the educational level is far higher than the EU average. Unmet need reduces in Portugal and Greece (by 0.4 p.p.), which have lower national levels of educational attainment than the EU average.

Column V in Table 10.2 further controls for variables measuring individual risk of poverty and unemployment, and is also illustrated by the green dots in Figure 10.2. These additional factors lead to small changes in unmet need, relative to column IV, in almost all countries (maximum 0.3 p.p. changes) except in Greece (–0.5 p.p.), Estonia and Latvia (–0.9 p.p. and –0.8 p.p. respectively).

Column VI in Table 10.2 includes deciles of household disposable income (in PPS values), in addition to age, gender, chronic condition, education, AROP and unemployment. This is also illustrated by the light blue dots in Figure 10.2 (as well as in Figure 10.1, as discussed above). Risk-adjusted unmet need is altered by the further inclusion of household disposable income as a control variable, especially for countries that have lower income in PPS terms than the EU average. In particular for Greece and eastern European countries (Estonia, Latvia,

Table 10.2: Unmet need, unadjusted and adjusted for age, gender, chronic condition, education, unemployment and AROP, income, EU-27 and United Kingdom, 2018
(%)

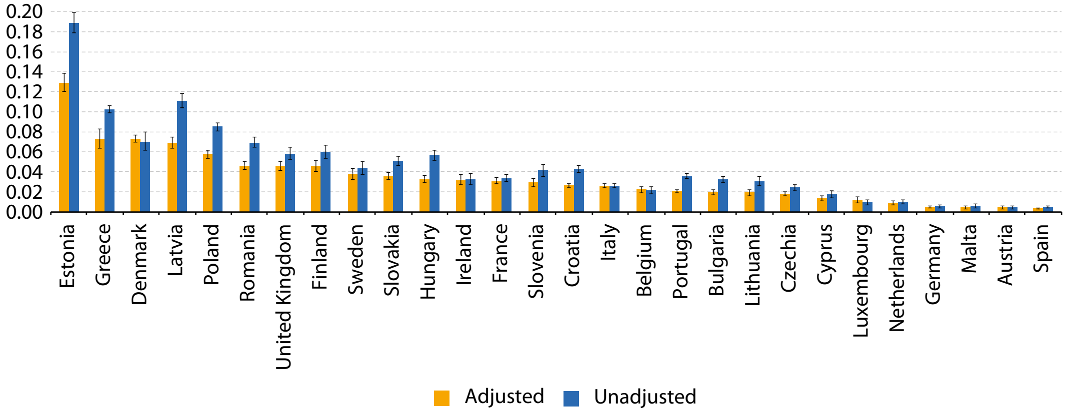
Model	I	II	III	IV	V	VI
Age and gender	-	Yes	Yes	Yes	Yes	Yes
Chronic condition	-	-	Yes	Yes	Yes	Yes
Education	-	-	-	Yes	Yes	Yes
Unemployment and AROP	-	-	-	-	Yes	Yes
Income	-	-	-	-	-	Yes
Austria	0.41	0.40	0.34	0.34	0.33	0.39
Spain	0.43	0.41	0.37	0.33	0.31	0.3
Germany	0.52	0.51	0.39	0.42	0.40	0.45
Malta	0.53	0.54	0.47	0.41	0.42	0.44
Netherlands	0.95	0.92	0.81	0.82	0.81	0.87
Luxembourg	0.96	0.95	0.89	0.85	0.83	1.17
Cyprus	1.70	1.73	1.39	1.36	1.28	1.31
Belgium	2.14	2.09	2.06	2.03	1.98	2.20
Czechia	2.42	2.25	2.00	2.11	2.12	1.78
Italy	2.58	2.47	2.86	2.61	2.52	2.55
Lithuania	3.06	2.97	2.61	2.74	2.48	1.93
Bulgaria	3.20	3.10	3.18	3.15	2.86	1.95
Ireland	3.28	3.31	3.05	3.02	2.90	3.18
France	3.36	3.29	2.77	2.75	2.75	3.08
Portugal	3.58	3.46	2.86	2.51	2.5	2.05
Slovenia	4.13	3.89	3.25	3.33	3.16	2.91
Croatia	4.25	4.15	3.65	3.62	3.34	2.59
Sweden	4.32	4.20	3.66	3.72	3.67	3.77
Slovakia	5.11	5.08	4.6	4.76	4.79	3.53
Hungary	5.66	5.53	4.69	4.74	4.74	3.29
United Kingdom	5.82	5.59	4.44	4.48	4.41	4.56
Finland	5.97	5.72	4.38	4.49	4.36	4.56
Romania	6.94	6.83	7.31	7.03	6.87	4.61
Denmark	7.01	6.80	6.30	6.50	6.59	7.33
Poland	8.48	8.25	7.13	7.37	7.28	5.75
Greece	10.23	9.91	10.4	10.00	9.52	7.29
Latvia	11.08	10.72	9.27	9.67	8.86	6.93
Estonia	18.89	18.25	15.04	15.78	14.93	12.91

Note: Dependent variable is whether the individual reports unmet need or not. Countries are listed in ascending order according to unadjusted unmet need in population in column I. Age is also included with quadratic and cubic functions, and these are interacted with gender. Income: annual equivalised disposable income adjusted for purchasing power standard categorised in deciles according to EU distribution.

Reading note: In Estonia, 18.9 % of the population report unmet need. This reduces after adjusting for the average EU value of (1) age and sex to 18.3 %, (2) age, sex and chronic condition to 15.0 %, (3) age, sex, chronic condition and education to 15.8 %, (4) age, sex, chronic condition, education, AROP and unemployment to 14.9 % and (5) age, sex, chronic condition, education, AROP, unemployment and income to 12.9 %.

Source: Authors' computations, UDB September 2019.

Figure 10.1: Unadjusted and adjusted unmet need, EU-27 and United Kingdom, 2018
(Unmet need at EU sample mean)

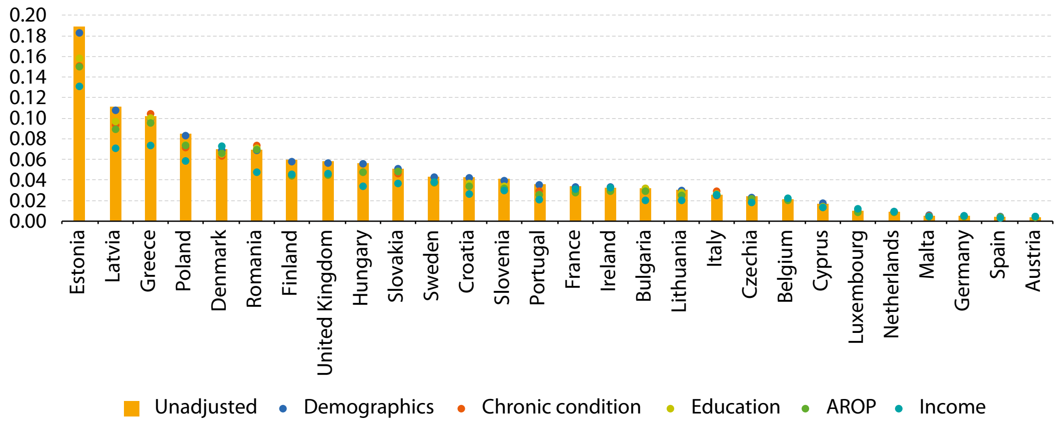


Note: Unadjusted unmet need in EU-27 and the United Kingdom (blue bars) and unmet need after adjusting for age, gender, chronic condition, highest educational attainment, AROP, unemployment and annual equivalised disposable income adjusted for PPS categorised in deciles (orange bars) with 95 % confidence intervals. Age is also included as quadratic and cubic functions; the quadratic and cubic functions of age are also interacted with gender. Countries are listed in descending order according to adjusted unmet need.

Reading note: In Estonia, 18.9 % of the population report (unadjusted) unmet need (blue bar). After adjusting for the average EU values of age, sex, chronic condition, education, poverty, unemployment and income, unmet need reduces to 12.9 % (orange bar). In contrast, in Spain, only 0.4 % of the population report (unadjusted) unmet need (blue bar), which reduces to 0.3 % after adjusting for all of the control variables (orange bar). In Estonia, the difference between unadjusted and adjusted unmet need is statistically significant, but this is not the case for all countries (e.g. Denmark and Ireland).

Source: Authors' computations, UDB September 2019.

Figure 10.2: Differences in unmet need, unadjusted and adjusted for different groups of controls, EU-27 and United Kingdom, 2018
(Unmet need at EU sample mean)



Note: Age is also included as quadratic and cubic functions, and the quadratic and cubic functions of age are also interacted with gender. Income is annual equivalised disposable income adjusted for PPS and is categorised in deciles according to the whole EU distribution. Logit specification. Countries are listed in descending order according to unadjusted unmet need.

Reading note: In Estonia, 18.9 % of the population report (unadjusted) unmet need (orange bar). This reduces to 18.3 % after adjusting for demographic variables: age, gender and age and gender interaction (blue dot), and to 15.0 % after adjusting for demographic variables and chronic condition (red dot); increases to 15.8 % after adjusting for demographics, chronic condition and highest educational attainment (light green dot); and reduces to 14.9 % after adjusting for demographics, chronic condition, education, AROP and unemployment (green dot), and to 12.9 % after adjusting for demographics, chronic condition, education, AROP and unemployment indicators and income (light blue dot).

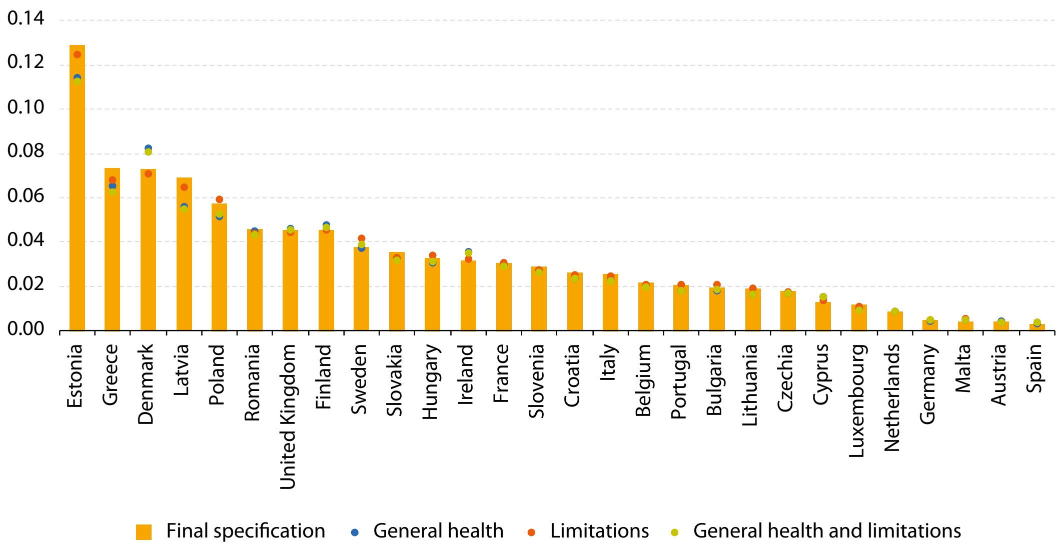
Source: Authors' computations, UDB September 2019.

Romania, Poland, Hungary and Slovakia), risk-adjusted unmet need significantly reduces by at least 1 p.p., relative to column V, after controlling for disposable income (ranging from 1.3 p.p. in Slovakia to 2.3 p.p. in Romania). It reduces by 0.6–0.9 p.p. in Croatia, Bulgaria and Lithuania, and by 0.3–0.5 p.p. in Czechia, Portugal and Slovenia. Risk-adjusted unmet need increases by 0.3 p.p. in France, Ireland and Luxembourg, and 0.7 p.p. in Denmark. Risk-adjusted and unadjusted unmet need estimates are similar for other countries, after controlling for disposable income (less than 0.2 p.p. variation).

10.4.3. Sensitivity analysis: additional health variables

We included self-reported general health, and limitation in activities because of health problems, to our final specification (column VI in Table 10.2). For the majority of countries, the results were unaffected by the inclusion of these variables (Figure 10.3). However, the inclusion of self-reported general health reduced unmet need in Estonia, Denmark and Latvia and increased unmet need in Greece. We provide this specification as a sensitivity analysis because we are concerned about possible reverse causality, with higher unmet need leading to poorer self-reported health and possibly greater limitation in activities. Moreover, health is affected directly by health systems through the provision of healthcare services, whereas the other variables (demographic, education, income) are not under direct control of the health system. In addition, we lose about one third of the observations for Lithuania because values for self-reported general health are missing.

Figure 10.3: Differences in unmet need, with inclusion of additional health variables, EU-27 and United Kingdom, 2018
(Unmet need at EU sample mean)

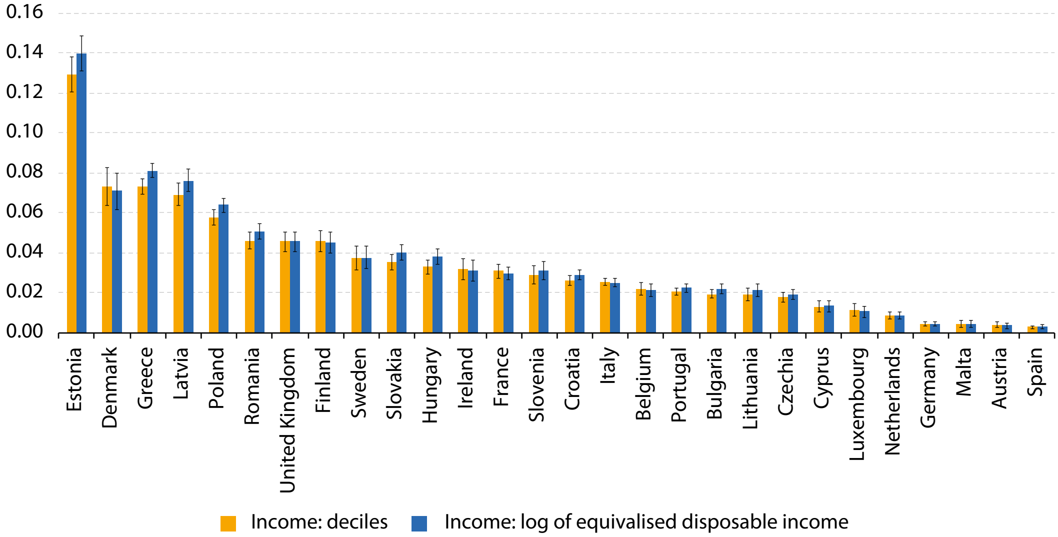


Note: Unmet need at EU average, logit specification. A variable measuring the interaction of age and gender is included, age is also included as quadratic and cubic functions, and the quadratic and cubic functions of age are also interacted with gender. Income is measured as the annual equivalised disposable income adjusted for PPS categorised in deciles according to the whole EU distribution. Countries are listed in descending order according to adjusted unmet need.

Reading note: In Estonia, unmet need adjusted for age and gender, chronic condition, highest educational attainment, AROP, unemployment and income is 12.9 % (orange bar). When self-reported general health status is added, unmet need reduces to 11.4 % (blue dot), whereas the addition of limitation in activities because of health problems reduces unmet need to 12.4 % (red dot). The addition of both variables reduces unmet need to 11.2 % (light green dot). In contrast, in Austria and Spain, the addition of these variables does not change unmet need, which remains at 0.4 % and 0.3 % respectively.

Source: Authors' computations, UDB September 2019.

Figure 10.4: Differences in unmet need with income measured in deciles and as the log of equivalised disposable income, EU-27 and United Kingdom, 2018
(Unmet need at EU sample mean)



Note: Unmet need after controlling for age, gender, chronic condition, highest educational attainment, AROP, unemployment and disposable income adjusted for purchasing power parity (PPP) with 95 % confidence intervals, logit specification. Control variables: (orange bar) age, gender, and age and gender interaction; age is also included as quadratic and cubic functions, and the quadratic and cubic functions of age are also interacted with gender; chronic condition, highest educational attainment, AROP, unemployment and annual equivalised disposable income adjusted for PPP and categorised in deciles according to the whole EU distribution. In blue bar, age, gender, and age and gender interaction; age is also included as quadratic and cubic functions, and the quadratic and cubic functions of age are also interacted with gender; chronic condition, highest educational attainment and (log of) annual equivalised disposable income measured as a continuous variable and adjusted for PPP. Countries are listed in descending order according to adjusted unmet need, with income measured as deciles.

Reading note: In Estonia, unmet need is 12.9 % when it is adjusted for income measured in deciles, which reflects the income distribution (in addition to the other control variables) (orange bar). Unmet need increases to 14 % when income is measured as a continuous variable with a logarithmic transformation (blue bar). However, the differences are not statistically significant.

Source: Authors' computations, UDB September 2019

10.4.4. Sensitivity analysis: equivalised disposable income

As an additional sensitivity analysis, in our preferred specification (column V in Table 10.2) we include equivalised disposable income in PPS measured as a continuous variable with a logarithmic transformation instead of deciles. Results are robust to this change in specification, as can be seen in Figure 10.4. The ranking according to unmet need is similar for the two models, and figures are not statistically different within countries except for Greece.

10.5. Conclusion

Self-reported unmet need for medical care is a practical and simple way of measuring access to care, and is commonly used in European countries (Allin and Masseria, 2009; OECD, 2019a). In this chapter, we investigate if unmet need differs across countries using EU-SILC data for 2018. We compare countries before and after adjusting for factors that are outside the control of the health system, such as demographic, education, AROP, unemployment and income variables.

Whereas many of these countries have low levels of unmet need, others, including Denmark and Sweden, have relatively high levels. Most of the control variables have a relatively modest impact on unmet need. Although risk adjustment resulted in reductions in unmet need in countries such as Estonia, Greece and Latvia, relatively high levels of unmet need remain after adjustment. These are likely to be due to structural issues across health systems that relate to barriers to access due to affordability, waiting lists or times, or physical accessibility. In order to investigate if this is the case, we analysed the reasons for unmet need. We found that 82 % of respondents in Greece felt that the main reason for unmet need was related to affordability (medical care was too expensive), whereas in Estonia 80 % of respondents stated that waiting lists were the main reason for unmet need (Table 10.A2). Unmet need may also arise from personal circumstances, knowledge, preferences and perceptions of healthcare, and this highlights the subjective nature of unmet need pointed out in Section 10.1. Again, there may be a role for policy intervention, for example by improving health literacy, especially among people with low socioeconomic, education and health status (EXPH, 2016). Owing to a lack of evidence on the factors that may influence self-reported unmet need, it is necessary to investigate how different individuals in different countries understand and interpret the questions on unmet need (EXPH, 2016).

The relationship between income and unmet need is well established in previous studies using EU-SILC (Chaupain-Guillot and Guillot, 2015; Elstad, 2016; Israel, 2016; Eurostat, 2010) but less so in relation to how income affects country comparisons on unmet need. Israel (2016) found that social allowances (means-tested benefits for households that fall into particular categories, for example single parents, or are eligible because of low household income) were associated with a reduction in unmet need for medical care for financial reasons. The author surmised that this was because social allowances provided a basic income to the lowest income group (first quintile) and increased income for the lower-middle-income group (second quintile). However, this may depend on the design of the social allowance and if it is targeted at the second income quintile, which is not the case in many countries. Similarly, Madureira-Lima et al. (2018) found that financial hardship had a mediating role on the relationship between unmet need and unemployment, implying that the reduction in income resulting from loss of employment led to an increase in unmet need. Our analysis shows that differences in annual equivalised disposable income within the EU play an important role in the comparison of unmet need across countries, relative to the differences in demographics or educational attainment. Consequently, differences in unmet need between countries are smaller after controlling for income, which allows for a more meaningful comparison of unmet need as a measure of health system performance.

Missing data on unmet need are an issue for the United Kingdom only, where we find 17 % of data missing. Respondents are equal in terms of income distribution and AROP, but those who do not report unmet need are, in general, males, younger, with intermediate education and without chronic conditions (Table 10.A3). Therefore, for the United Kingdom we are likely to be estimating a lower bound of unmet need, as unmet need increases for women and increases with age, lower levels of education and presence of chronic conditions.

Our analysis compares adjusted with unadjusted unmet need across EU countries. Adjusting unmet need for differences in demographics and socioeconomic factors that are outside the control of health systems improves the comparability of unmet need as a measure of health system performance on access in international comparisons. We find that, in general, most of these variables have a relatively modest impact on differences in unmet need across EU countries, except for household income. Although controlling for income reduces differences in unmet need across countries, marked and significant differences remain in several EU countries (Baltic States, Greece, Hungary, Poland and Romania). Although measuring unadjusted unmet need is important to assess the size of the access problem in the EU and all countries, there is also scope for measuring risk-adjusted unmet need to improve between-country comparisons for the purposes of health system performance assessment on access.

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Appendix 10.1: Unmet need question on SILC questionnaire

Eurostat defines a respondent as having unmet need if 'there was at least one occasion when the person really needed examination or treatment but did not receive it' (Eurostat, 2020a p. 273), and the aim of the variable is to capture restricted access to medical care. Eurostat recommends that the question should be implemented using a two-way approach with a filter before the unmet need question as follows:

> PH040_Q1: 'Was there any time during the past 12 months when you really needed medical examination or treatment (excluding dental) for yourself?
>
> Yes (I really needed at least at one occasion medical examination or treatment) [1];
>
> No (I did not need any medical examination or treatment) [2].
>
> FILTER: If PH040_Q1 = 1 then GO TO PH040_Q2.
>
> PH040_Q2: Did you have a medical examination or treatment each time you really needed?
>
> Yes (I had a medical examination or treatment each time I needed) [1];
>
> No (there was at least one occasion when I did not have a medical examination or treatment) [2].' (Eurostat, 2020a p. 274)

This two-step procedure is summarised using the following flags in PH040_Q2:

> 1 Filled (PH040_Q1 = 1)
>
> –1 Missing
>
> –2 Not applicable: the person did not really need any medical examination or treatment (PH040_Q1=2)
>
> –3 Non-selected respondent

However, it seems that some countries do not follow Eurostat's recommendation. Table 10.A1 shows for each country (1) the probability of being in unmet need for the total population – that is, those who answered 'Yes' to PH040_Q2 are included in the numerator, and general survey respondents are included in the denominator – and (2) the probability of being in unmet need conditional on having experienced need for medical care – that is, those who answered 'Yes' to PH040_Q2 are included in the numerator and those who answered 'Yes' to PH040_Q1 are included in the denominator, thereby excluding those who did not really need any medical examination or treatment (PH040_Q1 = 2, which are the ones with flag = –2).

For some countries (Austria, Denmark, Estonia, Ireland, Portugal, Slovakia and the United Kingdom) the two proportions are equal, meaning that (1) all respondents experienced need for medical care or (2) respondents were not asked the question on medical need before unmet need, with (2) appearing to be the more realistic option.

Table 10.A1: Conditional and unconditional probabilities of experiencing unmet need, 2018
(%)

Country	Unmet need, not conditional on reporting need	Unmet need, conditional on reporting need
Austria	0.4	0.4
Belgium	2.1	2.7
Bulgaria	3.2	5.9
Croatia	4.2	6.2
Cyprus	1.7	2.1
Czechia	2.4	2.9
Denmark	7.0	7.0
Estonia	18.9	18.9
Finland	6.0	8.3
France	3.4	3.9
Germany	0.5	0.8
Greece	10.2	23.3
Hungary	5.7	8.4
Ireland	3.3	3.3
Italy	2.6	5.5
Latvia	11.1	15.0
Lithuania	3.1	4.4
Luxembourg	1.0	1.2
Malta	0.5	1.1
Netherlands	1.0	2.9
Poland	8.5	14.6
Portugal	3.6	3.6
Romania	6.9	8.2
Slovakia	5.1	5.1
Slovenia	4.1	5.5
Spain	0.4	0.6
Sweden	4.3	8.1
United Kingdom	5.8	5.8

Reading note: In Sweden, 4.3 % of all respondents reported unmet need for medical care. However, unmet need increases to 8.1 % among respondents who reported a need for medical care. In the United Kingdom, 5.8 % of all respondents reported unmet need for medical care, the same percentage as among those who reported a need for medical care, implying either that all respondents needed medical care or that no respondents were asked if they needed medical care.

Source: Authors' computations, UDB September 2019.

Table 10.A2: Reasons for unmet need, 2018
(%)

Country	Adjusted unmet need	Affordability	Waiting lists	Physical accessibility	Other reasons
Spain	0.0030	13.7	24.2	—	62.1
Austria	0.0039	22.4	3.9	1.9	71.8
Malta	0.0044	10.9	19.2	—	69.9
Germany	0.0045	16.2	15.0	4.9	63.9
Netherlands	0.0087	10.0	13.2	1.3	75.6
Luxembourg	0.0117	27.0	5.1	—	67.8
Cyprus	0.0131	80.9	1.9	0.8	16.4
Czechia	0.0178	1.9	5.6	5.2	87.3
Lithuania	0.0193	13.4	54.3	3.7	28.6
Bulgaria	0.0195	46.3	2.5	9.5	41.7
Portugal	0.0205	44.7	10.2	2.5	42.6
Belgium	0.0220	80.4	0.9	0.6	18.1
Italy	0.0255	77.1	14.3	0.7	7.8
Croatia	0.0259	11.5	6.5	16.2	65.9
Slovenia	0.0291	2.7	80.7	0.6	15.9
France	0.0308	21.1	12.7	0.6	65.6
Ireland	0.3180	40.0	45.3	0.7	14.0
Hungary	0.0329	5.4	5.5	3.3	85.9
Slovakia	0.0353	13.5	28.5	6.7	51.3
Sweden	0.0377	2.1	37.3	—	60.6
Finland	0.0456	0.3	84.0	0.4	15.3
United Kingdom	0.0456	2.1	52.1	2.3	43.4
Romania	0.0461	49.2	13.9	6.9	29.9
Poland	0.0575	13.4	33.0	3.0	50.6
Latvia	0.0693	38.3	12.7	4.8	44.2
Greece	0.0729	81.6	3.2	1.5	13.7
Denmark	0.0733	3.6	13.7	1.0	81.6
Estonia	0.1291	3.0	79.7	4.1	13.1

Reading note: In Estonia, 3.0 % of respondents reported that the main reason for unmet need was affordability of care (too expensive), 79.7 % waiting lists, 4.1 % physical accessibility (too far to travel or no means of transport) and 13.1 % other reasons (e.g. no time because of work or caring for children or others, fear of healthcare, waited to see if problem would resolve, did not know good doctor or specialist).

Source: Authors' computations, UDB September 2019.

Table 10.A3: **Characteristics of respondents with non-missing and missing data on unmet need, United Kingdom, 2018**
(%)

Variable	Mean, non-missing subsample	Mean, missing subsample
Unemployment: 0 months (%)	96.9	94.6
Unemployment: 1–6 months (%)	1.2	1.8
Unemployment: 7–11 months (%)	0.5	0.3
Unemployment: 12 months (%)	1.4	3.4
Age	49.7	36.4
AROP: no (%)	82.6	84.0
AROP: yes (%)	17.4	16.0
Chronic conditions: no (%)	54.7	72.2
Chronic conditions: yes (%)	45.3	27.8
Education: high (%)	43.1	35.2
Education: intermediate (%)	31.2	42.0
Education: low (%)	25.7	22.8
Gender: female (%)	53.7	39.4
Gender: male (%)	46.3	60.6
Income (disposable), 1 000 PPS	22.8	24.0

Reading note: Considering the UK data, compared with respondents who responded to the question on unmet need, those who did not respond to this question were more likely to be unemployed for 12 months (3.4 % versus 1.4 %), younger (36.4 years versus 49.7 years) and at comparable risk of poverty (16 % versus 17.4 %), less likely to have a chronic condition (27.8 % versus 45.3 %), and more likely to have an intermediate level of education (42 % versus 31.2 %), be male (60.6 % versus 46.3 %) and have a comparable level of income (GBP 24 000 versus GBP 22 800).

Source: Authors' computations, UDB September 2019.

11 Excess mortality among people at risk of poverty or social exclusion: results for five EU countries

Johannes Klotz, Matthias Till and Tobias Göllner ([138])

11.1. Introduction

Excess mortality among lower socioeconomic classes is a common phenomenon in present-day European populations and perhaps the ultimate evidence of persisting health inequalities. Previous studies of many European countries have found considerable excess mortality among lower socioeconomic classes, which are most often operationalised by low educational level, and in some instances by low occupation-based social class or low income (see Mackenbach et al., 2016, and the references given therein).

Some common findings in differential mortality research are:

- variation in mortality risk is not merely caused by some marginal groups, but present throughout the social ladder (ONS, 2020; Lampert and Kroll, 2014);
- disparities are larger among men than women (Luy et al., 2015; Schumacher and Vilpert, 2011);
- disparities are larger in eastern than in western Europe (Mosquera et al., 2019; Corsini, 2010);
- relative disparities become smaller, but not zero, with increasing age – it is noteworthy that, even among the oldest, inequalities in mortality between social classes are observed (Klotz et al., 2019; Reques et al., 2015).

Most published studies refer to results for single countries and are based on a linkage of census records (or population registers) with mortality records in follow-up periods. The objective of this chapter is to reach beyond previous research by estimating excess mortality figures for five countries (1) drawing from a comparative social classification of poverty and social exclusion (see Chapter 1 for a definition of the EU AROPE indicator and its components) and (2) using sample data collected from EU-SILC. To the best of our knowledge, this is the first study on mortality disparities using EU-SILC observations from several countries. On the advantages and disadvantages of using sample survey data for estimating inequalities in mortality, see Klotz and Göllner (2017).

It is important to clarify at this point that 'excess mortality' is meant here in a purely descriptive sense: mortality risk in one group is statistically higher than in another group. To what degree this inequality is avoidable, or if it is unfair and therefore a call for political action, is beyond the scope of our chapter. One may refer to the important work of Fleurbaey (2008) for such questions. It may however be noted that systematic variation in life expectancy remaining after retirement may cause considerable lifetime income redistribution from the poor towards the rich (Knell, 2018).

The second section of this chapter describes in detail the materials and methods applied, with a special focus on the innovative data source and the statistical model. Section 11.3 presents the results for Belgium, Bulgaria, Spain, Latvia and Austria,

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disaggregating by sex, age groups and the components of AROPE. The final section discusses the main findings, strengths and weaknesses of the study and gives some outline for further research.

11.2. Materials and methods

11.2.1. The at risk of poverty or social exclusion target group

The AROPE target group combines people who are AROP and/or suffer from SMD and/or QJ, as explained in Chapter 1. A person belongs to the AROPE target group if they fulfil at least one out of these three criteria. For those fulfilling at least two criteria, we use the term 'intersection' subgroup of AROPE. Although this is not an official European definition, enhanced poverty can be assumed among the intersection subgroup.

11.2.2. Data acquisition, pooling and preparation

For our analysis we use a data set that was created specifically for our purposes by experts from five countries ([139]). The authors explained in detail to the national experts the data structure necessary for such an analysis, and the experts arranged the data for their countries and transmitted them to the authors. The content of the data was limited to the needs of our analysis, so no socioeconomic variable other than AROPE was requested. Some countries (Belgium, Latvia and Austria), however, also delivered the three components of AROPE as separate indicator variables.

We use cross-sectional EU-SILC data augmented with mortality information from national mortality registers in follow-up periods. We use not the EU-SILC longitudinal information on vital status, which is subject to measurement error at micro level and health-related panel attrition at macro level (Klotz and Göllner, 2017), but hard evidence on deaths obtained from official mortality registers based on mandatory death certificates. The survey of Klotz and Göllner (2017) across European NSIs revealed that most European countries would technically be in a position to link cross-sectional EU-SILC data with mortality registers, but only a minority of them have ever done it.

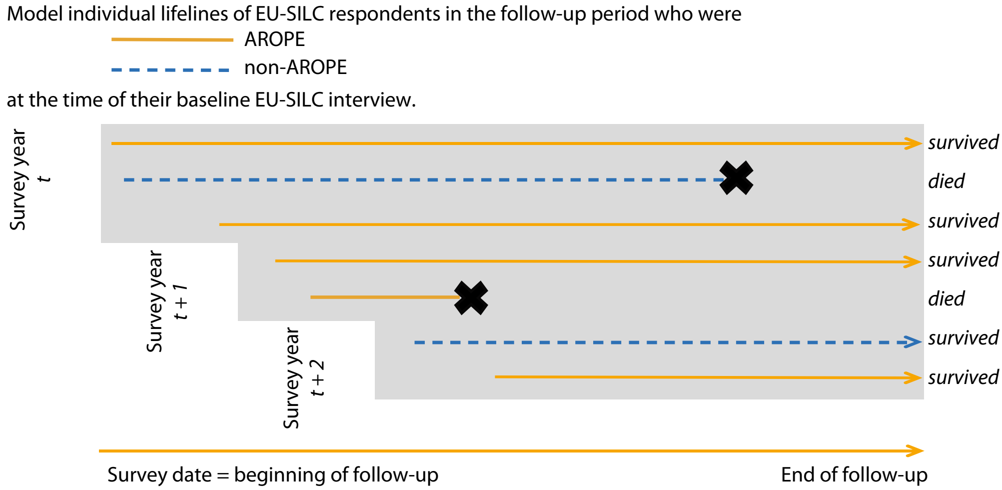
To increase statistical reliability, cross-sectional EU-SILC data were pooled over several survey years in such a way that each person is included exactly once in the data set. For example, in the Belgian case we joined all EU-SILC survey respondents interviewed in 2008 with the respondents interviewed for the first time in 2009, 2010, 2011 or 2012. Linkage with national mortality registers was done by the countries providing the data and was done deterministically with unique personal identifiers. To continue the Belgian case, linkage was done with all deaths in Belgium until 31 December 2014. AROPE information and all covariates were measured at the first available interview per person (the baseline interview). So, for every survey respondent ever interviewed in the EU-SILC baseline years, we can determine if they (1) belonged to the AROPE group in the baseline survey year and (2) survived or died during the follow-up period ([140]). Figure 11.1 illustrates data pooling and linkage by lifelines (from survey date to either death or censoring) for seven EU-SILC survey respondents.

Data preparation and all statistical analyses were done with SAS, Version 9.4. The SAS code is available from the authors on request.

([139]) The authors would very much like to thank the following national experts for their help, cooperation and data provision: Rana Charafeddine, Stefaan Demarest and Françoise Renard (Scientific Institute of Public Health, Belgium); Magdalena Kostova and Sergey Tsvetarsky (Statistics Bulgaria); Jose Maria Mendez (INE, Spain); Baiba Zukula and Martins Liberts (Statistics Latvia).

([140]) In practice, the 'survivors' most likely also include some respondents who have left the country, plus some linkage errors.

Figure 11.1: Illustration of data pooling and linkage



Reading note: In this figure, we illustrate the individual lifelines (horizontal) of seven EU-SILC respondents: three respondents interviewed in year t, two respondents first interviewed in year t + 1 and another two respondents first interviewed in year t + 2.

The lifeline for each survey respondent begins with the date of their (first) EU-SILC interview and ends when they either die (illustrated by a cross) or are still alive at the end of the period for which national mortality records are complete ('survived').

Information on death versus survival is obtained from national mortality registers, whereas all other information (age, sex, poverty status, etc.) is obtained from cross-sectional EU-SILC records (which are, in this case, pooled over 3 survey years). The lengths of the lifelines (times at risk; measured in time units such as years or months) are thus available as such neither in the EU-SILC records nor in the mortality records, but are to be computed after matching the two data sources.

Out of the seven respondents, five survive and two die in the follow-up period. Out of the five survivors, one was AROPE and four were non-AROPE at their baseline interviews. Out of the two deceased respondents, one was AROPE and the other one was non-AROPE at their baseline interviews. The total length of the lifelines (added up over the seven respondents) is the person-years lived in the follow-up period.

Source: Own illustration.

11.2.3. Countries included

Our data cover five different countries: Belgium, Bulgaria, Spain, Latvia, and Austria (Figure 11.2). This selection of countries is meaningful for differential mortality analysis because:

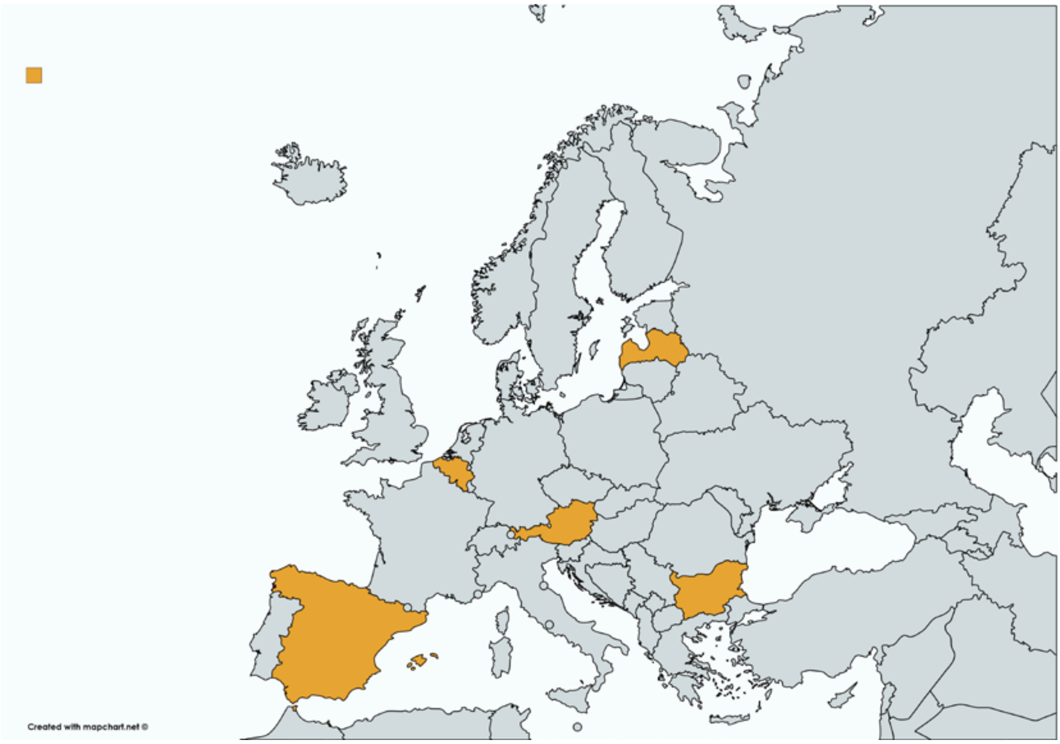
- it covers a wide range of AROPE prevalence, from less than 20 % in Austria to more than 30 % in Bulgaria (Table 11.1);
- different welfare state models ([141]) are represented;
- both western and eastern Europe are covered.

The last point is particularly important in mortality analyses, since life expectancy has evolved fundamentally differently in eastern Europe, and even more so in the former Soviet Union, from in western Europe over the last 50 years (see Timonin et al., 2017, and the references given therein).

In all countries included, EU-SILC has a regular rotation of 4 years, meaning that in each year around a quarter of the cross-sectional sample is refreshed with new survey respondents.

([141]) Since the seminal book by Esping-Andersen (1990), an enormous volume of research has been published on welfare state typologies, especially regarding European countries, and how they relate to economic and social outcomes. Although we do not apply any particular such typology in this chapter, most researchers might agree that Belgium and Austria, which are usually seen as instances of a 'Corporatist/Conservative' welfare state, are somewhat closer in their welfare state models than Belgium and Spain.

Figure 11.2: Map of the countries included in the analysis



Reading note: The orange countries are included: Belgium, Bulgaria, Spain, Latvia, Austria.

Source: Own illustration created with mapchart.net.

Table 11.1: Prevalence of AROPE and its components, 2018

(% of total population)

Country	Non-AROPE	AROPE	Only 1 AROPE component			2+ components
			AROP	SMD	QJ	
Belgium	80.0	20.0	8.6	0.9	2.4	8.1
Bulgaria	67.2	32.8	9.1	9.2	1.2	13.3
Spain	73.9	26.1	14.4	1.6	2.7	7.4
Latvia	71.6	28.4	15.2	3.8	1.1	8.3
Austria	82.5	17.5	10.3	0.9	2.0	4.3

Reading note: In Belgium in 2018, 80.0 % of the population were non-AROPE and the remaining 20.0 % were AROPE. The AROPE population can be further disaggregated into 8.6 % AROP only, 0.9 % SMD only, 2.4 % QJ only and 8.1 % in the intersection subgroup, for which at least two out of the three AROPE components are true.

Source: Eurostat database, ilc_pees01, accessed on 30 August 2020.

11.2.4. Sample characteristics

After pooling the five countries together, our sample covers more than 180 000 distinct individuals who were between 30 and 79 years old at their baseline interview. The age range was restricted for modelling purposes and out of analytical interest. Table 11.2 gives the details on the sample per country. Altogether the total of person-years is more than 1 million and the total of deaths exceeds 10 000. The country sample is largest in Spain (because of the greater EU-SILC sample size for this large country) and smallest for Belgium and Bulgaria (because of the shorter follow-up periods and smaller EU-SILC samples).

Mortality follow-up usually ends with a calendar year, except for Latvia, where the first three quarters of 2018 were also included. The number of deaths is highest in Latvia, reflecting its relatively high general mortality level and the long follow-up period. Crude death rates are much higher in eastern than in western Europe.

As mentioned above, our data cover all individuals ever interviewed in the EU-SILC baseline years, thus the entire sample of the first baseline year and the in-rotating parts of the cross-sectional samples in the following years (Table 11.3). See Chapter 17 of this volume on some impacts of this procedure.

Table 11.2: Sample characteristics

Country	SILC baseline years	Mortality follow-up until	Population aged 30–79 at baseline			Crude death rate (per 1 000)
			Individuals	Person-years lived	Deaths	
Belgium	2008–2012	31 Dec 2014	17 646	94 694	795	8.4
Bulgaria	2011–2015	31 Dec 2015	20 426	68 096	1 148	16.9
Spain	2008–2016	31 Dec 2017	77 240	480 287	3 576	7.4
Latvia	2008–2017	30 Sep 2018	32 872	206 305	3 688	17.9
Austria	2008–2017	31 Dec 2017	32 601	187 794	1 432	7.6
Total			180 785	1 037 176	10 639	**10.3**

Reading note: The crude death rate is the ratio of deaths to 1 000 person-years lived.

Source: EU-SILC data linked with national mortality registers. Linkage was done by the countries.

Table 11.3: Number of individuals by country and EU-SILC baseline year, 2008–2017

Country	Individuals first interviewed in										Total
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
Belgium	9 193	2 597	2 159	1 920	1 777	—	—	—	—	—	17 646
Bulgaria	—	—	—	11 377	2 207	2 057	2 436	2 349	—	—	20 426
Spain	22 396	7 305	6 784	6 411	6 545	6 648	6 230	6 434	8 487	—	77 240
Latvia	8 100	2 989	3 081	2 999	2 799	2 533	2 530	2 695	2 775	2 371	32 872
Austria	8 223	2 912	2 860	2 599	2 588	2 639	2 785	2 608	2 721	2 666	32 601

Reading note: The data include 17 646 individuals from Belgium. Of them, 9 193 were interviewed in 2008, another 2 597 were first interviewed in 2009, another 2 159 were first interviewed in 2010, another 1 920 were first interviewed in 2011 and the remaining 1 777 individuals were first interviewed in 2012.

Source: EU-SILC data linked with national mortality registers.

For each of the 180 785 individuals, the following variables are included in our data set:

- country,
- date of the survey interview ([142]),
- sex,
- age at survey interview (in completed single years, i.e. a continuous variate),
- vital status (died or survived),
- date of death or censoring,
- person-years lived (the difference in years between the date of the survey interview and the date of death or censoring),
- AROPE and, as far as provided by the countries, its components,
- cross-sectional weight (RB050).

11.2.5. Proportional hazards regression

Excess mortality in the AROPE target group was estimated on a relative scale by Cox regression mortality hazard ratios (Kleinbaum and Klein, 2010). In this semiparametric model the instantaneous mortality hazard of individual *i* at time *t* of follow-up is

$$h_i(t) = h_0(t) \times exp\,(a \times AGE_i + b + SEX_i + c \times AGE_i \times SEX_i + d \times AROPE_i), \qquad (11.1)$$

with $h_0(t)$ a nonparametric reference hazard and $exp(d)$ the mortality hazard ratio of AROPE versus non-AROPE. When the model is stratified by sex, then parameters *b* and *c* are zero. Such models are commonly used in medicine, but so far less so in demography.

The key outcome in this chapter is $exp(d)$, the excess mortality of AROPE compared with non-AROPE. For example, $exp(d) = 1.5$ means that there are 50 % more deaths in a certain time period in the AROPE population than would occur in a non-AROPE population of the same size and age–sex makeup.

([142]) When not the exact survey date but only the month and year of the survey was available in the data, then the day of the survey was imputed as the 15th day of the month.

Another useful outcome of the model in equation (11.1) is the ratio *d/a*, since this can be understood as the equivalent (in terms of mortality risk) of the number of additional years of age at baseline compared with being AROPE. For instance, if this ratio is 5, then an individual aged 40 and non-AROPE at baseline has the same instantaneous mortality risk as an individual (of the same sex) aged 35 and AROPE at baseline. This ratio gives thus a crude estimate of the life expectancy disadvantage of the AROPE target group members.

11.3. Results

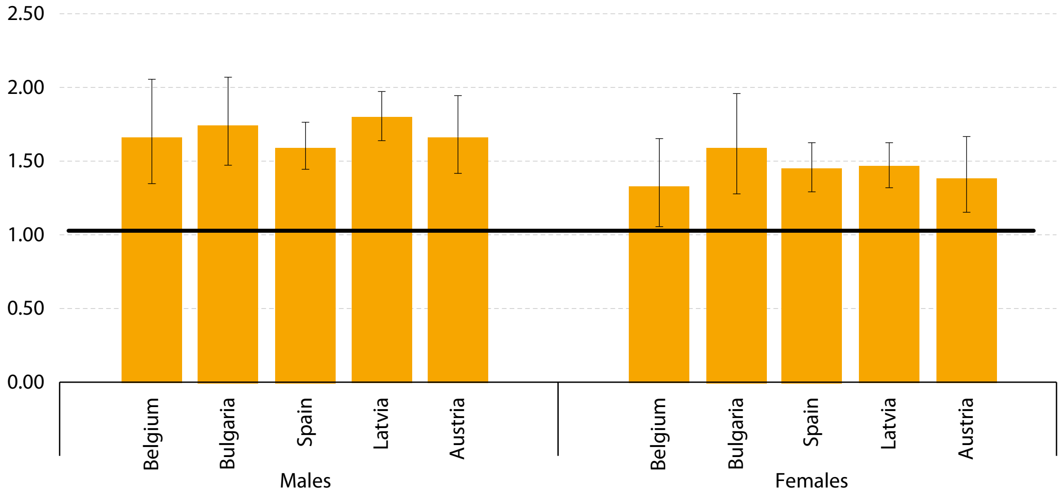
11.3.1. Model for all age groups

The model in equation (11.1) was estimated stratified by country and sex. Estimated mortality hazard ratios are given in Figure 11.3. We see that AROPE comes with a significant excess mortality, and in each country this effect is greater among men than women. The unweighted average of the mortality hazard ratios across the five countries is 1.69 for males and 1.44 for females. Both estimates are significantly greater than 1 ($p < 0.001$ each), and the degree of excess is significantly different between men and women ($p = 0.001$). Our study thus confirms the long-known findings in differential mortality research that the poor die earlier, and that sex is a mediator in this relationship in the sense that the disadvantage of poor men is especially large.

To illustrate our figures, assume a population of non-AROPE males out of whom 100 die over a certain time period. Then, in a population of AROPE males of the same size and age structure, one observes not 100, but 169 deaths over the same period.

Perhaps surprisingly, there is no clear statistical relationship between excess mortality (Figure 11.4) and AROPE prevalence, despite huge variation in the AROPE prevalence (Table 11.1) between the five countries. Excess mortality estimates for Austria and Bulgaria, the countries with the lowest and highest AROPE prevalences, are statistically indistinguishable. Apparently being AROPE has very similar consequences (in terms of excess mortality) across different European countries.

Figure 11.3: Estimated mortality hazard ratio of being AROPE versus non-AROPE
(by sex)



Note: Estimates refer to people aged 30–79 years at baseline, are controlled for age and are weighted with cross-sectional weight (RB050).

Reading note: The bold line at 1.00 indicates the mortality hazard of each non-AROPE group. Error bars indicate 95 % confidence intervals. A mortality hazard ratio of 1.5 means that, in an AROPE population, 50 % more deaths occur over a certain time period than in a non-AROPE population of the same sex, size and age structure.

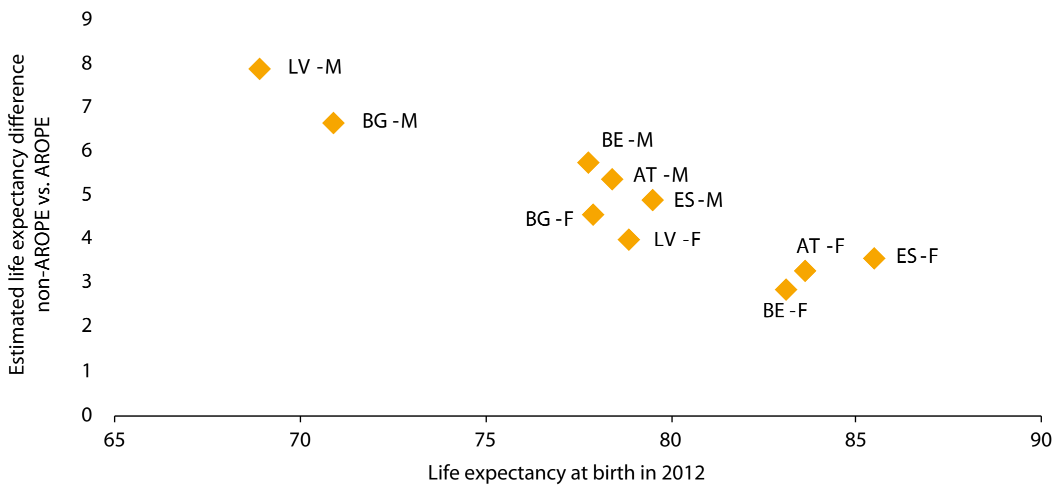
Source: EU-SILC data linked with national mortality registers.

However, similar mortality hazard ratios between countries may still have different meanings in terms of life expectancy loss in those countries. This is because the association between mortality hazard ratio and life expectancy difference is in general non-linear and depends on the age-mortality risk pattern in a country (Keyfitz and Caswell, 2005, ch. 4).

The estimated life expectancy disadvantages ([143]) range from 5.4 to 7.9 years among males (unweighted country average 6.1 years) and from 2.9 to 4.6 years among females (unweighted country average 3.7 years). Figure 11.4 plots the estimated life expectancy disadvantage against the life expectancy at birth values in 2012, which is approximately the middle of our observational period. A negative statistical correlation is clearly visible: the higher the life expectancy disadvantage among the AROPE target group, the lower the general life expectancy level in a population. Life expectancy in eastern Europe could thus be boosted by both reducing the AROPE prevalence and improving the relative mortality risk of the target group.

([143]) For Belgian males, the parameters in equation (11.1) are estimated as follows: $a = 0.089$, $d = 0.511$, $b = c = 0$. Thus, mortality risk increases by a factor of,so by 9.3 % with each additional year of age at baseline. So being 2 years older means a 19.4 % higher mortality risk (1.093^2), 3 years older means a 30.5 % higher mortality risk (1.093^3) and so on. The excess mortality associated with AROPE is,so mortality risk is 66.6 % higher when AROPE than when not AROPE and of the same age (this figure is shown in Figure 11.3). The ratio,so being AROPE has the same impact on mortality risk as being 5.8 years older at baseline (and of the same AROPE status). In other words, a Belgian male aged 30 and AROPE has the same instantaneous mortality risk as a Belgian male aged 35.8 and not AROPE. In yet other words, AROPE comes with a 5.8-year disadvantage in life expectancy. (This is only a crude estimate, for it assumes the effect of AROPE on relative mortality risk to be constant across all ages.)

Figure 11.4: General life expectancy and estimated AROPE life expectancy disadvantage by country and sex
(years)



Reading note: See Appendix 2 for a list of country abbreviations. Following the country codes, 'M' indicates males and 'F' indicates females. In Latvia, AROPE males have an estimated life expectancy disadvantage of 7.9 years compared with non-AROPE peers, although in this country all males (AROPE and non-AROPE) have an average life expectancy at birth of 68.9 years.

Sources: EU-SILC data linked with national mortality registers; Eurostat database, demo_mlexpec, accessed on 3 January 2020.

11.3.2. Age-specific analysis

It is well known in demographic research that relative mortality rate ratios between socioeconomic groups decline with increasing age (see Reques et al., 2015, and the references given therein). Two major reasons for this are increasing absolute mortality levels with age and selective survival among the lower socioeconomic groups. In the AROPE case, age-specific analysis is especially important because one of the three components of AROPE, namely QJ (very low work intensity), matters only for people (non-students) of working age. We thus estimate separate models (males and females combined) for ages 30–59 and 60–79 at baseline.

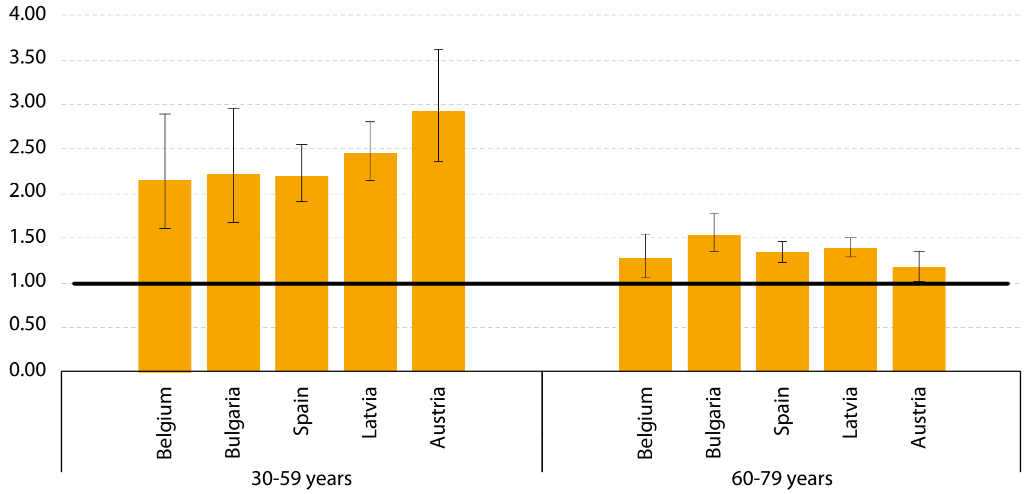
Figure 11.5 confirms the decline of mortality rate ratios for the AROPE population compared with the non-AROPE population with increasing age. At working ages, estimated Cox regression hazard ratios range between 2.2 and 2.9, whereas at retirement ages the range is from 1.2 to 1.5 (all estimates are significantly greater than 1). Estimated differences between countries are small, are statistically insignificant and show no clear pattern. In short, it is age and not country that matters for the excess mortality statistically associated with AROPE.

11.3.3. Disaggregation of at risk of poverty or social exclusion into its components (ages 30–59 years)

Given that the AROPE excess mortality is greater at working ages, when all three components of AROPE apply ([144]), we further investigate the effects of different subgroups of AROPE on mortality risk. We estimated a model in the same fashion as in equation (11.1), but with the binary AROPE indicator replaced with a five-level categorical variable. The reference category is again the non-AROPE population, which is now compared with the following groups (see Figure 11.1 and Table 11.1).

([144]) A referee suggested an even more fine-tuned approach, namely to restrict the analysis to individuals from households with at least one working-age member. Although we agree that this would be the best filter, we cannot apply it to our data, since they do not contain household identifiers (see Section 11.2.4).

Figure 11.5: Estimated mortality hazard ratio of AROPE versus non-AROPE by age group (age at baseline)

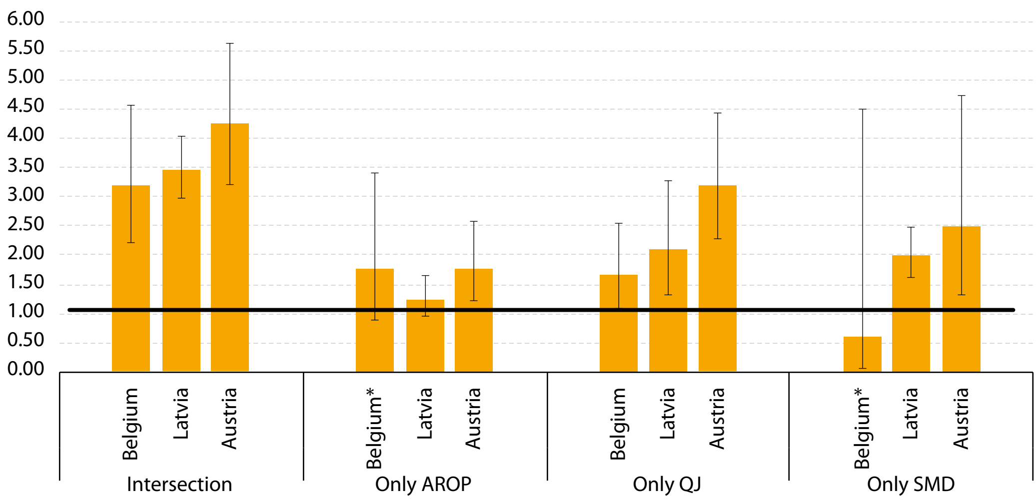


Note: Estimates are controlled for age and sex and weighted with cross-sectional weight (RB050).

Reading note: The bold line at 1.00 indicates the mortality hazard of each non-AROPE group. Error bars indicate 95 % confidence intervals.

Source: EU-SILC data linked with national mortality registers.

Figure 11.6: Estimated mortality hazard ratio of AROPE versus non-AROPE by subgroup (ages 30–59)



Note: Estimates are controlled for age and sex and weighted with cross-sectional weight (RB050).

Reading note: The bold line at 1.00 indicates the mortality hazard of the non-AROPE group in each country. Error bars indicate 95 % confidence intervals. The distance between the upper bound of the confidence interval and the point estimate is larger than between the lower bound and the point estimate because our model (see equation (11.1)) is non-linear and the confidence interval limits are exponentiated. For example, if the point estimate is 1.2 and the lower bound is 0.6 (half the point estimate), then the upper bound is 2.4 (twice the point estimate). *, estimated hazard ratios based on fewer than 20 deaths.

Source: EU-SILC data linked with national mortality registers.

- The intersection subgroup of respondents who meet at least two out of the three AROPE criteria (AROP, QJ and SMD). This may be an 'enhanced poverty' subgroup, which covers roughly 30 % of the entire AROPE population.
- The subgroup of respondents who are only AROP, and suffer from neither QJ nor SMD. This is usually the largest subgroup of the entire AROPE population.
- The subgroup of respondents who suffer from only QJ, not SMD, and are not AROP.
- The subgroup of respondents who suffer from only SMD, not QJ, and are not AROP. This is usually a small subgroup in western Europe, but much larger in some eastern European countries.

Note that, because of data availability, this analysis is feasible only for Belgium, Latvia and Austria. Estimated mortality hazard ratios are given in Figure 11.6. As expected, excess mortality is amplified for the intersection subgroup, where mortality risk is three to four times as high as in the non-AROPE reference group. Among the 'only' subgroups, it seems that QJ is rather hazardous for health (this would also, to some degree, explain the smaller hazard ratios at retirement ages).

11.4. Conclusions

In this chapter we have investigated the statistical relationship between AROPE and mortality risk, based on a special data set, which was built by pooling various countries' cross-sectional EU-SILC data that were linked with death records from national mortality registers in follow-up periods. Our analysis covers five different countries representing widely varying AROPE prevalences, different welfare state regimes, and both western and eastern Europe.

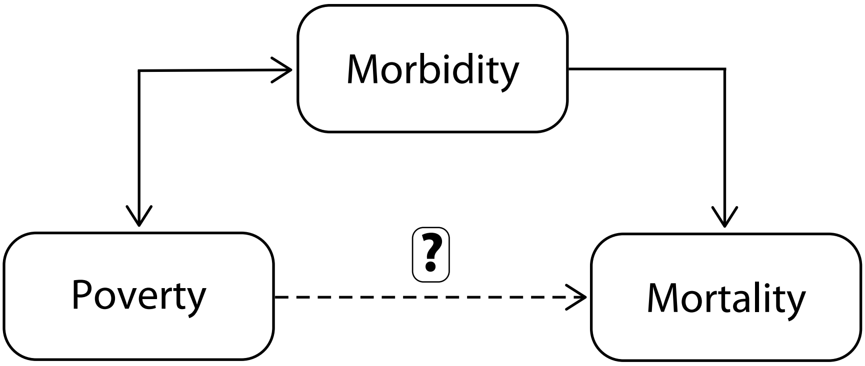
To the best of our knowledge, this is the first attempt to estimate the impact of AROPE on mortality risk, especially in a cross-country perspective. Our central findings are:

- AROPE comes with significant excess mortality in all countries;
- the degree of excess mortality is virtually unrelated to the AROPE prevalence in a country;
- excess mortality is more pronounced among males than females and more pronounced at working than retirement ages (which is in line with usual demographic findings);
- as expected, excess mortality is amplified for people who fit more than one of the three AROPE criteria.

The direction of the relationship between poverty and mortality risk is not straightforward. First, a lack of material resources may come with limitations in access to healthcare. Although this should be a smaller problem in European countries, which have virtually universal health insurance coverage, than for example in the United States, even in European countries there may be issues with out-of-pocket payments, waiting times or non-take-up that may affect the poor disproportionately. But it is also the case that some groups with particularly high mortality risks, such as the chronically ill, are more likely to be AROP or suffer from SMD or QJ. Since morbidity is the key mediator in this relationship, it might be of interest to control for health limitations when estimating excess mortality of the poor (Figure 11.7). Such a model was estimated by Klotz et al. (2018), who found that around 40 % of excess mortality of severely materially deprived Europeans can be statistically attributed to excess health-related limitations in daily activities.

A limitation of our study is the pure cross-sectional covariate measurement, which may not properly capture the dynamic nature of the mediation effect. A more realistic approach, which is based on longitudinal data, is given by Majer et al. (2011), who use data from EU-SILC's predecessor, the European Community Household Panel. They found that socioeconomic status is a strong predictor of age at onset of disability, but less important as a predictor of mortality risk when disability is already present. In general, when interpreting the results, one should acknowledge that we are measuring AROPE at the EU-SILC baseline, not the 'cumulative exposure' of being AROPE over time, which would produce stronger results for people who are AROPE in the long term, as was confirmed by Till et al. (2018).

Figure 11.7: Causal relationships between morbidity, mortality, and poverty and social exclusion



Source: Own illustration.

Another interesting finding of our chapter is that, although there is huge variation both in AROPE prevalence and in general mortality levels between western and eastern Europe, the estimated mortality hazard ratios of the AROPE population are comparable in all five countries. This resembles the findings of Klotz et al. (2018) on excess mortality by SMD. Regarding variation in mortality differentials by educational level, however, Corsini (2010) found much greater inequalities in eastern than western European countries.

More research is needed to ascertain the impact of being AROPE on mortality risk at individual (intra-household) level. For instance, our results seem to suggest a role for QJ. It remains, however, unclear if this equally affects all household members' mortality risks. The literature indicates that individual experience of (long-term) unemployment has a major impact on health outcomes on its own (regarding mortality, see Martikainen and Valkonen, 1996; Moser et al., 1984).

One limitation of our chapter is that the only covariates included are age and sex. Future research should therefore extend the number of covariates, including for instance individual labour market participation. EU-SILC is an exceptional data set in this respect, since it covers many individual socioeconomic indicators (e.g. education or occupation), the Minimum European Health Module, and household and family characteristics in a harmonised way. Estimation of partial effects, ideally exploiting longitudinal EU-SILC information on changes in risk factors over time, might substantially increase our understandings of the mechanisms linking poverty and mortality risk.

Another obvious extension would be to increase the number of countries included. As indicated above, the survey of Klotz and Göllner (2017) across European NSIs revealed that more than 20 European countries would technically be in a position to link cross-sectional EU-SILC data with mortality registers, but fewer than 10 have ever done it. The benefit of covering additional countries would be not just increasing the sample size, but also opening up the possibility of grouping countries by welfare state models and testing if the effect of poverty on mortality risk is mediated by them.

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12 Improving our knowledge of housing conditions at EU level

Ida Borg and Anne-Catherine Guio (145)

12.1. Introduction

The aim of this chapter is to study the variations between EU countries in a large range of housing problems derived from EU-SILC data and to examine to what extent these between-country differences can be explained by measurable factors, at either micro or macro level.

This chapter builds on previous research, mainly that of Borg (2015), who was the first to propose a multilevel framework to study housing deprivation across EU countries in order to examine the role of the structure and organisation of the housing market in housing deprivation. It extends this analysis by analysing many different housing dimensions: severe housing deprivation, overcrowding, leaking roof, darkness of the dwelling and two different concepts of housing cost overburden.

It is organised as follows. In the next section, we specify our expected patterns at micro and macro levels. In Section 12.3, we present in more detail our expectations regarding the impact of the housing market on housing outcomes. Section 12.4 presents our methodology and the variables used in the analyses. Section 12.5 presents the results from multilevel analyses. The chapter ends with a concluding section.

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12.2. Micro-level determinants of housing problems

Previous research shows that the situation across EU Member States is very heterogeneous when it comes to poor housing conditions (Borg, 2015; Mandic and Cirman, 2012; Norris and Shiels, 2007; Stephens et al., 2015; Dewilde and De Decker, 2016; Dewilde, 2017).

Most of the previous studies identified distinct groups of countries in this respect: northern EU Member States, where housing conditions are enviable; continental countries, with relatively good housing conditions; southern countries, with less good housing conditions; and central and eastern European Member States, with poor housing conditions (Norris and Shiels, 2007; Mandic and Cirman, 2012). These groups of countries differ in terms of the socioeconomic characteristics of the population, the level of affluence of the population, the welfare state regime and the roles of public and privately owned/rented housing. We are interested in both micro-level determinants and macro-level factors. Each of these levels will be discussed below.

As far as micro-level determinants are concerned, in line with earlier findings in the housing literature, we argue that housing problems depend on similar micro-level risk factors to those highlighted in the extensive literature on material deprivation. In contrast to the risk factors identified in the analysis of income poverty, which mainly relates to factors linked to current income (education, labour participation, provision of social transfers), the risk factors for material/housing deprivation are linked to both long-term resources and needs/costs (Perry, 2002; Fusco et al., 2010; Nolan and Whelan, 2011; Notten and Guio, 2020; Whelan and Maître, 2006, 2007; Verbunt and Guio, 2019). So, on one side, resources are defined in a broader sense than in income poverty analysis, closer to the 'permanent income' concept, which is determined by past, current and future income and accumulated savings/debts (see an extensive discussion by Guio et al., 2020, and Chapters 8 and 13 of this book). On the other side, households with equal resources may have different needs and face different costs, depending on their health status, family composition (education and childcare costs), material support from family, friends and neighbours, and the availability of in-kind services.

Our hypothesis is thus that the individual- or household-level risk factors include factors related to permanent income, costs and needs, household size and type. In contrast to previous studies of housing conditions (Borg, 2015), we opt for including household income at micro level, because it is the best predictor of permanent income available in the data set. An important contribution of this study is that including household income might have an impact on the conclusions regarding the roles of some of the macro-level determinants.

12.3. Macro-level determinants of housing problems

Housing problems can be explained by household risk factors but also have specific (macro) determinants linked to the particular nature of the housing 'commodity'. Indeed, the supply and demand sides of housing have a major influence on housing comfort and cost. Furthermore, past decisions concerning housing policies, public investment in different housing types, quality of housing stock and localisation create path dependence and impact on the current state of available dwellings and their price and quality (Malpass, 2011; Bengtsson and Ruonavaara, 2010, 2011).

As highlighted by Stephens et al. (2015), the recent housing literature can be broadly separated into studies that attempt a direct application of the Esping-Andersen theory of welfare state regime to housing, and those that have followed Kemeny's (1995) housing regime typology. The latter group includes papers that showed that the tenure-based structure of the housing stock affects housing outcomes (see, among others, Borg, 2015; Dewilde, 2017; Dewilde and De Decker, 2016; Mandic and Cirman, 2012). 'Housing regimes' is a broad concept, which consists of 'constellations of power relationships, ideological beliefs and cultural patterns referring to the social, political and economic organisation of the provision, allocation and consumption of housing' (Kemeny, 1981, elaborated by Dewilde and De Decker, 2016, p. 121). Kemeny argued that there are two distinct models of housing: home-owning and cost-rental societies. The first system is dominated by homeownership; the social rental sector is generally small and dedicated to the most disadvantaged households. The second system has, in contrast, a large proportion of renters, it is more integrated and the rent is linked to the cost of provision rather than to the market value (Dewilde and De Decker 2016). Furthermore, Mandic and Cirman (2012) analysed the role of two specific housing models: the 'Central-Eastern' model and the 'Southern' model. The first model is historically marked by a state-controlled housing sector. Prior to the transition to a market economy, housing conditions were worse in these countries than in western countries for a variety of reasons linked to the planned economy (Mandic and Cirman, 2012, p. 783), despite what several authors called an overconsumption of resources by the housing system, which was unsustainable but led to housing conditions better than those that would be expected on the basis of GDP level. The transition process led to a boom in homeownership by sitting tenants through privatisation schemes (Stephens et al., 2015) but tended to worsen the housing conditions, owing to lack of maintenance and of housing investment.

In the southern housing system, the family played an important role. A high proportion of housing ownership replaced an adequate social safety net. However, the quality of housing was constrained by financial resources in this system, owing to lack of access to the financial market. These two regimes are characterised by a high proportion of outright owners.

These papers tend to show that the housing regime has an impact on housing quality. Nevertheless, as Dewilde (2017, p. 386) pointed out, 'although European housing regimes can and have been qualified in terms of the levels and forms of state intervention versus the role of the markets and families, they are hard to capture in a quantitative way'. Comparative studies in housing policy that apply typologies may be questionable, as they seriously reduce the between-country variation we are interested in understanding (Kasza, 2002; Abrahamson, 1999). A way to reveal the descriptive information that is hidden in these typologies is to use contextual or institutional measurements on a continuous/interval scale. Borg (2015) proposed such a pathway and showed that the cost-rental integrated system, as measured by the size and organisation of the rental sector, is more successful in reducing housing deprivation than the dual rental system dominated by high homeownership.

Borg (2015) suggested three mechanisms explaining why integrated rental systems are more successful in reducing housing deprivation. First, integrated rental systems promote low homeownership rates, as the rental sector is seen as a viable option for all income groups (Kemeny, 1995; Voigtländer, 2009). Elsinga and Hoekstra (2005) argue that, in countries with a well-developed rental sector with high security of tenure, a rental dwelling is seen as a very acceptable alternative to homeownership and attracts higher income groups. Consequently, households within the home-owning sector are believed to belong to middle- and high-income groups, and thus are able to maintain their housing (Norris and Shiels, 2007; Mandic and Cirman, 2012). Second, in integrated rental systems, the private and the public rental sectors compete for the same segments in the population. This competition might lead to better housing quality (Kemeny et al., 2005; Dewilde, 2017). Third, one explanation for successful (income) poverty alleviation in universal welfare states is the pooling of risks and resources (Korpi and Palme, 1998; Marx et al., 2012; Kenworthy, 1999; Kenworthy et al., 2011; Brady and Bostic, 2015). As integrated rental sectors aim to encompass broader income groups than selective solutions such as social housing, the same mechanisms are believed to apply when it comes to reducing housing deprivation.

Korpi and Palme (1998) suggested that targeted welfare systems increase homogeneity among the recipients of social insurance; that is, only the poorest households are included, and these households tend to have similar levels of risks and resources. Universal welfare systems, on the other hand, pool risks and resources across broader income groups. By adding heterogeneity and including in the welfare state services middle- and high-income earners who could afford the same services on market terms, the support for public programmes and redistributive policies is strengthened. This is believed to lead to transfers and services of higher quality than those programmes only encompassing the poor. Thus, we hypothesise that the structure and organisation of the housing market is important and, most notably, that the organisation of the rental sector is crucial for understanding the prevalence of housing deprivation.

This leads us to test the hypothesis, as in Borg (2015), that integrated rental systems are more successful in reducing the prevalence of housing problems. Furthermore, we hypothesise that countries with a large proportion of outright owners experience higher housing deprivation, overcrowding and housing cost overburden. The proportion of outright owners in a country is considered here as a crude indicator of historical and institutional factors that affect the availability and quality of housing, and characterise some eastern and southern regimes (for an extensive discussion see Norris and Shiels, 2007). It is worth keeping in mind that outright ownership can result from very different public policies, as explained by Dewilde (2017), that is, either public policy that encourages homeownership or, at the opposite end of the scale, inadequate housing and welfare policies, which lead people to rely on their own and their family's resources.

This means that data on tenure status enter into the model twice. At household level, the individual tenure status of the household in the model will show how renters compare with owners in terms of risk of housing problems. At macro level, the national tenure structure of the housing market is expected to have an impact on the general level of housing deprivation and housing costs in the country and on the differences between countries (see Borg, 2015).

12.4. Method and data

12.4.1. Method

We used the 2015 EU-SILC UDB, covering 32 countries and almost 600 000 individuals. The unit of analysis was the individual, as for the computation of EU social indicators in the housing domain. The population of reference includes all people living in these 32 countries, without age restriction.

We ran multilevel regressions to take into account the fact that individuals were clustered at national level. Multilevel regression analysis takes into account the fact that this creates dependency between the country level and the individual level. If not taken into account, this dependency would bias the standard errors of the regression coefficients (Borg, 2015).

As all our dependent variables are dummies, we used logistic multilevel regression. The Stata xtmelogit command was used, with mixed-effects models for binary outcomes.

12.4.2. Dependent variables

We analysed a large range of dependent variables covering different aspects of housing deprivation and housing cost overburden.

- **Severe housing deprivation.** According to the EU definition, a household is defined as experiencing it if that household is living in a dwelling that is simultaneously:
  - overcrowded (i.e. if the household does not have at its disposal a minimum number of rooms equal to one room for the household, one room per couple in the household, one room for every single person aged 18 or more, one room per pair of single people of the same gender between 12 and 17 years of age, one room for every single person between 12 and 17 years of age and not included in the previous category or one room per pair of children under 12 years of age); and
  - exhibiting at least one of the following housing deprivation problems:
    - a leaking roof, damp walls, floors or foundation, or rot in window frames or floor,
    - no bath/no shower, nor indoor toilet,
    - darkness.

The aggregated indicator, as well as each of these subcomponents, is analysed separately when the sample size allows.

- **Housing cost overburden.** According to the EU definition, a household suffers from high housing cost overburden when its total housing costs (net of housing allowances) represent more than 40 % of disposable income (net of housing allowances) ([146]). In the literature, such an 'objective' measure is compared with a 'subjective' assessment of the housing cost overburden, based on a question in which the respondent self-assesses whether or not the total housing costs represent a financial burden. Thus, we also included a subjective housing cost overburden variable, which is coded 1 if the respondent has answered that the housing costs are a heavy burden to them.

It is worth emphasising that some aspects of housing comfort, such as the quality of the broader residential area where people live, are not included in the analysis. Table 12.1 presents our dependent variables.

([146]) Housing costs include mortgage interest payments (net of any tax relief) for owners; rent payments gross of housing benefits for renters; and housing benefits for rent-free households. They also include structural insurance, mandatory services and charges (sewage removal, refuse removal, etc.), regular maintenance and repairs, taxes and the cost of utilities (water, electricity, gas and heating). They do not include capital repayment for mortgage holders. Housing allowances include rent benefits (a current means-tested transfer granted by the public authorities to tenants, temporarily or on a long-term basis, to help them with rent costs) and benefits to owner-occupiers (a means-tested transfer by public authority to owner-occupiers to alleviate their current hosing costs; in practice, they also often include help with mortgage reimbursements (Social Protection Committee, 2015).

Table 12.1: Severe housing deprivation rate and its components, overcrowding rate, objective and subjective housing cost overburden rates by country, 2015
(%)

Country	Severe housing deprivation	Over-crowding	Leaking roof	No bath/ shower	No indoor toilet	Dwelling too dark	Housing cost over-burden	Subjective housing cost over-burden
Cyprus	1	1	27	1	1	5	4	72
Norway	**1**	**5**	**7**	**0**	**0**	**3**	**10**	**5**
Finland	1	7	4	1	1	4	5	20
Belgium	1	2	18	1	2	7	9	30
Netherlands	1	3	16	0	0	5	15	10
Ireland	1	3	14	0	0	6	5	35
Malta	1	4	10	0	0	7	1	34
Spain	2	6	15	0	0	4	10	58
Switzerland	2	6	12	0	0	7	12	26
Luxembourg	2	7	14	0	0	7	6	34
Germany	2	7	13	0	0	4	16	14
Sweden	2	12	8	1	0	6	8	7
United Kingdom	2	7	15	1	0	5	13	25
France	2	7	13	1	1	8	6	26
Iceland	3	8	19	0	0	3	10	25
Denmark	3	8	16	2	1	3	15	9
Estonia	3	13	13	7	7	5	7	20
Czechia	3	19	9	0	1	4	10	24
Slovakia	4	38	6	1	1	3	9	30
Austria	4	15	12	1	1	6	6	14
Portugal	5	10	28	2	1	8	9	37
EU	5	17	15	2	2	6	11	34
Slovenia	6	14	27	1	0	6	6	32
Greece	7	28	15	1	1	6	41	47
Croatia	7	42	11	2	2	5	7	62
Lithuania	9	26	17	12	12	5	9	30
Italy	10	28	24	0	1	7	9	58
Poland	10	43	12	3	3	4	9	61
Bulgaria	11	41	13	12	19	6	15	41
Hungary	16	41	25	4	4	9	9	31
Latvia	16	41	24	15	14	9	8	31
Serbia	17	53	23	4	4	8	29	71
Romania	20	50	13	31	33	6	16	36

Note: Countries are ranked according to their level of housing deprivation.
Reading note: In Cyprus, more than 70 % of people suffer from subjective heavy housing cost overburden.
Source: Authors' computations, UDB September 2017.

Across the EU-27 as a whole, 5 % of the population suffered from severe housing deprivation in 2015. There were five EU Member States where this proportion was higher than 10 %: Bulgaria (11 %), Hungary, Latvia (16 % each), Serbia (17 %) and Romania (20 %). By contrast, 1 % or less of the population in Cyprus, Norway, Finland, Belgium, Netherlands, Ireland and Malta faced severe housing deprivation.

Table 12.1 also presents the proportion of people living in overcrowded dwellings. This again masks large national variation, from less than 5 % in Cyprus (1 %), Belgium (2 %), the Netherlands, Ireland (3 % each) and Malta (4 %) to around 50 % in Romania and Serbia.

Table 12.1 also presents the national proportions of people living in a household suffering from high housing cost overburden. Greece appears extreme in the chart, with a housing cost overburden rate higher than 40 %, followed by Serbia (29 %). Most of the other countries have an overburden rate ranging between 5 % and 15 %. Cyprus and Malta have the lowest rates. Bulgaria, Denmark, the Netherlands, Germany and Romania suffer from the highest proportions (after Serbia and Greece), close to 15 %. From Table 12.1 we can also see the discrepancy between the subjective and objective measures of housing cost overburden rate, with Cyprus being an extreme example, namely among the best performers in terms of the objective measure and the worst using the subjective one.

One general conclusion of this overview is that there are sharp differences among EU countries, whatever the indicators on which we focus. An obvious pattern, also found previously, emerges too: the housing problems are more prevalent in eastern and, partly, southern Europe than in western and northern Member States.

12.4.3. Micro-level determinants

At individual level we controlled for age, divided into seven groups: 0–29, 30–39, 40–49 (reference), 50–59, 60–69, 70–79 and 80+ years.

At household level, we took the following into account.

- The equivalised disposable household income (logarithm), converted into PPS.
- The highest educational attainment achieved by all household members. Educational attainment was grouped into three categories: low, medium and high. Low education includes pre-primary, primary and lower secondary education; medium education includes (upper) secondary education; and high education combines education levels higher than (upper) secondary education.
- The QJ of the household, coded 1 if the household members worked less than 20 % of their potential during the income reference year. This variable is available for people aged 0–59 years old. Thus, people above 59 are considered not to suffer from QJ (i.e. coded as 0).
- The presence of at least one self-employed household member in order to take account of measurement difficulties of self-employment income, as well as eventual difficulties in differentiating private and professional expenses.
- The household type: single parent; two adults with one, two or three children; other households with children; two adults without children; and other households without children. Single households are the reference category.
- The tenure status, where outright owner is the reference category, compared with owner with a mortgage, renter paying reduced rate and renter paying prevailing prices.
- Two health-related variables indicating if at least one household member suffers from health problems. The first variable is based on a subjective assessment of the member's own health. The household member has health problems if they answered that their health is bad or very bad. The second variable is based on limitations in daily activities due to health problems. The household member has health problems if they answered that they are strongly limited or limited by health problems.
- The subjective assessment of the debt burden, as a proxy for negative wealth. Two dummies are included measuring if the household is experiencing a heavy debt burden or some degree of debt burden.
- The migration status to take into account differences in access to the housing market

(eventual discrimination) and differences in the generation of resources (lower wage level etc.). Two dummy variables measure if at least one member of the household has non-EU citizenship and if at least one member of the household is born outside the EU.

12.4.4. Macro-level determinants

Our first concern was how to measure the structure of the housing market. Like most of the empirical studies looking at the impact of different housing regimes, we simply used the distribution of home-ownership and renting to identify different housing regimes.

In EU-SILC, the tenure status has five modalities: outright owner; owner with a mortgage; tenant or subtenant paying rent at the prevailing or market rate; tenant or subtenant paying a reduced rate (lower than the market price); and rent-free tenant. Following Borg (2015), we aggregated these variables at country level.

As in Borg (2015), the three modalities of renting are used to proxy three different types of rental systems. The higher the proportion of renters paying at the prevailing or market rate, the more integrated the rental sector is supposed to be. The higher the proportion of renters paying at a reduced rate, the more the system supports social housing. The proportion of tenants renting for free was also incorporated. Our strategy differed from Borg (2015) in that we also distinguish between the proportions of owners with and without mortgages, so that we could identify housing markets where the family/state historically played an important role in providing homeownership (i.e. countries with a large proportion of outright owners) and the western system dominated by high homeownership (with mortgage).

We also investigated the impact of other macro variables related to the welfare system.

- The proportion of total social benefits in GDP included sickness/healthcare, disability, family/children, unemployment, pension, survivor, housing and all social exclusion benefits not classified elsewhere, and was derived from the Eurostat ESSPROS database.
- In addition, following Verbunt and Guio (2019) and Guio et al. (2020), we distinguished between in-cash and in-kind social spending, in percentage of GDP. These variables measured the generosity level of the welfare state in the country
- We also tested the impact of the adequacy of minimum income provisions (as in Guio et al., 2020). The indicator used is computed by the OECD and is based on the minimum income benefit for a married couple with two children, expressed as a percentage of national median household income. The minimum income includes cash housing assistance.
- We investigated the impact of access to financial markets based on the indicator developed by the European Mortgage Federation (2017), which is the share of outstanding residential loans in GDP. This indicator captures the importance of the finance market, relative to total economic activity; to some extent, it could be an indicator of financial depth.
- We also tested the relationship between the national level of affluence and the occurrence of housing problems (using the median income level derived from EU-SILC data, which is conceptually a better measure of the macro level of household affluence than the conventional GDP per capita used in similar analyses).

12.5. Results from multilevel analyses

In this section, we present the results from a number of multilevel regression analyses. We start by focusing on the micro-level determinants.

In Table 12.2, we compare the results from random intercept multilevel logistic regression analyses of the severe housing deprivation indicator; each of the indicators included in the housing deprivation measure([147]) (overcrowding, leaking roof, a dwelling being too dark); and the objective and subjective housing cost overburden measures.

([147]) 'Lack of basic amenities (no bath/shower)' is excluded from Table 12.2 owing to small sample size.

Before comparing the micro-level determinants of the housing problems in Table 12.1, we looked at 'empty' models to establish how much variation in the prevalence of housing problems can be explained by country-level factors. Almost 27 % of the variation in severe housing deprivation rates can be explained by country-level factors. About the same amount of between-country variation is found for the prevalence of leaking roofs. Regarding variation in overcrowding, 31 % can be explained by country-level factors. The lowest between-country variation is found in experiencing a dark dwelling, at 4 %. Interestingly, the between-country variation in housing cost overburden is 13 % for the objective measurement, while 20 % of the variation in subjective assessment of housing cost can be attributed to country-level factors.

12.5.1. Micro-level determinants

It is noteworthy that the factors related to the household resources and their costs/needs have the expected impact on all the different dimensions of housing (housing deprivation, its subcomponents, subjective housing cost overburden). These results can be summarised as follows (see Table 12.2 M1–M6).

- Household income has a strong and significant protective impact on the different housing problems studied. This confirms that this crucial variable has to be included in the model specification, even when the focus is on macro-level factors.
- Having a low educational level increases the risk of housing problems, even once the impact of the current income is taken into account. This may be explained by the link between education and future income, wealth and other variables that are not available in the data set but influence permanent income.
- Household QJ increases the risk of all housing problems. People living in QJ are more vulnerable in the housing market because of their vulnerability on the labour market, even once the impact of income is taken into account.
- Households where there is at least one self-employed member have a lower risk of facing housing problems. This is a usual result in material deprivation analysis (see Chapters 8, 13 and 15 of this volume). This may be due to the difficulty of correctly collecting self-employment income and adequately splitting personal and business costs. That may also be the reason why self-employed people face a higher housing objective cost overburden (as the denominator, i.e. income is underestimated), but fewer subjective housing cost risks than households where there is no self-employed member.
- People declaring a heavy debt overburden have higher risks of facing housing problems. Debt burden is a proxy for lack of wealth and (dis) saving.
- People aged 50 years or more face fewer housing problems than the reference group (40–49 years). Children and adults aged less than 30 face a higher risk.
- Homeowners with mortgages suffer from higher housing costs than households living in other tenure types, although they are better positioned in terms of other housing problems. Renters (prevailing price or reduced price) are more likely than outright owners to suffer from all housing problems.
- People facing health problems are also more likely to suffer from housing problems. This may be due to high health costs and poor prospects in terms of permanent income. The causality can also go in the opposite direction, as bad housing conditions have on impact on health.
- Those born outside the EU have a higher risk of suffering from housing problems, either because they face discrimination in access to the housing market or because they have lower permanent incomes.
- Compared with singles, families with children face a higher risk of overcrowding problems and severe housing deprivation, but a lower risk of suffering from dark housing. Regarding the housing cost burden, single people face significantly greater problems than all other household types according to the objective measure, although the opposite is true when the subjective measure of housing cost overburden is used. The risk factors linked to the household

type differ for the two indicators of housing cost overburden.

- These results show that the objective housing cost overburden measure has a particular pattern of risk. Indeed, some risk factors go in the opposite direction (household type, self-employment, health limitations). This raises the question of the definition of this indicator (see also Bowen and Clark, 2018; Clark and Bowen, 2018; Dewilde and De Decker, 2016; Stone, 2006).

12.5.2. Macro-level determinants

We now explore the extent to which the organisation of the housing market may explain differences in housing deprivation and housing cost overburden across countries.

The hypothesis regarding the role of the housing market structure was that integrated rental systems are more successful in reducing housing problems, as found by Borg (2015) ([148]). The literature review also indicated that countries with a large proportion of outright ownership would experience more housing problems, as the proportion of outright ownership is a crude indicator of historical and institutional factors that affect the availability and quality of housing in most eastern and southern regimes.

In Table 12.2, we present the models that take the housing market structure into account. Our results confirm our hypothesis that countries with a higher proportion of outright owners suffer from more severe housing deprivation and overcrowding than other countries. Our results do not, however, confirm our hypothesis that a large rental sector has a protective impact on housing deprivation. This important result sheds new light on previous results (e.g. Borg, 2015). Indeed, once the proportion of outright owners is explicitly included in the model (Borg, 2015, made no distinction between outright and mortgaged owners), the other variables related to the housing market structure (proportion of renters at prevailing market price, size of social housing sector), which had a (significant) negative impact on housing deprivation when the proportion of outright owners was omitted, are no longer significant. This could mean that the conclusion about the protective impact of a large rental sector was mainly driven by the fact that countries with large rental sectors are also those with low proportions of outright owners. Following this, it might not be the size of the rental sector per se that explains between-country variation in housing deprivation, but instead the historical, political and social circumstances that led to a high proportion of outright ownership in some parts of Europe (mostly southern and central/eastern Europe).

The final results concern the possible impact of other macro determinants on housing deprivation (Tables 12.3 and 12.4). These results indicate that all the variables related to the social benefits system, that is, in-cash transfer levels, in-kind transfers level and adequacy of social transfers, have a protective impact on housing deprivation, overcrowding and subjective housing cost overburden, as expected. The impact of in-kind benefits can be explained by the fact that the households that benefit from public services have lower personal costs and higher available income for housing consumption. Even though social transfers in cash are already taken into account at micro level through the household income, we do find a significant impact of in-cash benefits. We did expect that the adequacy of the minimum income scheme would protect people from housing deprivation, overcrowding and housing cost overburden, and this was confirmed by our results. Finally, the level of country affluence (as measured by the median income) has a strong influence on housing deprivation, overcrowding and subjective housing cost overburden.

Most of these variables have no significant impact on the objective housing cost burden, which confirms that the definition of this indicator deserves further investigation. The proportion of outstanding residential loans to GDP is negatively associated with housing deprivation, overcrowding and the subjective housing cost overburden, confirming that countries where access to financial markets is extensive suffer from less deprivation than others. National affluence is also negatively significantly associated with the occurrence of housing problems at EU level.

([148]) It should be noted, however, that Borg (2015) only studied housing deprivation, whereas we extend this analysis to cover housing problems related to the other dimensions.

Table 12.2: Random intercept multilevel logistic regressions of different housing problems, micro-level determinants, 32 countries, 2015

Independent variables	M1. Severe housing deprivation	M2. Overcrowding	M3. Leaking roof	M4. Dwelling too dark	M5.Housing cost overburden	M6. Subjective housing cost overburden
Age (years):						
0–29	0.170***	0.157***	0.080***	0.071***	0.128***	0.028***
30–39	0.0	−0.057***	0.056***	0.066***	0.106***	−0.029**
40–49 (ref.)	1.0	1.0	1.0	1.0	1.0	1.0
50–59	−0.153***	−0.307***	0.0	−0.050**	0.0	0.0
60–69	−0.394***	−0.626***	−0.183***	−0.167***	0.156***	−0.032**
70–79	−0.546***	−0.742***	−0.248***	−0.299***	0.0	−0.117***
80+	−0.479***	−0.595***	−0.325***	−0.316***	−0.081***	−0.268***
QJ	0.440***	0.236***	0.214***	0.238***	0.673***	0.403***
Education:						
Low	1.088***	0.443***	0.482***	0.403***	0.037**	0.466***
Medium	0.495***	0.309***	0.138***	0.130***	0.136***	0.300***
High (ref.)	1.0	1.0	1.0	1.0	1.0	1.0
Self-employed	−0.080***	−0.318***	−0.054***	−0.122***	0.591***	−0.252***
Household type:						
Single parent	1.056***	1.140***	0.187***	−0.139***	−0.514***	0.593***
2 adults, 1 child	0.594***	0.443***	0.0	−0.189***	−1.285***	0.049***
2 adults, 2 children	0.805***	0.781***	−0.038**	−0.274***	−1.462***	0.069***
2 adults, 3 children	1.687***	1.722***	0.259***	−0.065**	−1.689***	0.303***
Other with children	1.606***	1.938***	0.160***	−0.120***	−2.121***	0.221***
2 adults, no child	−0.291***	−0.648***	−0.081***	−0.165***	−1.167***	−0.193***
Other, no children	0.968***	0.921***	0.075***	−0.229***	−1.967***	0.119***
Single household (ref.)	1.0	1.0	1.0	1.0	1.0	1.0
Tenure status:						
Owner with a mortgage	−0.263***	−0.210***	−0.060***	0.0	0.770***	0.789***
Renter at prevailing prices	0.921***	1.091***	0.417***	0.555***	1.903***	0.781***
Renter at reduced prices	0.894***	0.808***	0.446***	0.551***	0.524***	0.198***
Outright owner (ref.)	1.0	1.0	1.0	1.0	1.0	1.0
Health problems	0.316***	0.137***	0.364***	0.343***	0.031**	0.501***
Health limitations	0.288***	0.053***	0.380***	0.277***	0.0	0.290***
Household disposable income (log) (PPS)	−0.222***	−0.204***	−0.171***	−0.134***	−1.308***	−0.596***
Heavy household debt	0.464***	0.150***	0.544***	0.374***	0.146***	1.529***

Independent variables	M1. Severe housing deprivation	M2. Overcrowding	M3. Leaking roof	M4. Dwelling too dark	M5.Housing cost overburden	M6. Subjective housing cost overburden
Somewhat heavy household debt	0.056***	−0.040***	0.204***	0.154***	−0.233***	−0.218***
Non-EU citizenship	0.174***	0.319***	0.0	0.086**	0.252***	0.111***
Non-EU country of birth	0.371***	0.441***	0.071***	0.150***	0.319***	0.282***
Intercept	−3.106***	−1.285***	−0.725***	−1.996***	9.861***	3.885***
Log likelihood	−97 269.6	−194 268.3	−241 003.6	−119 789.1	−140 137.4	−299 775.9
Intra-class correlation (ICC)	0.3	0.4	0.1	0.0	0.1	0.2
ICC empty model	0.3	0.3	0.3	0.0	0.1	0.2
N	594 139	593 802	594 039	594 139	590 167	592 296

Note: **, $p < 0.05$; ***, $p < 0.01$.

Source: Authors' computations, UDB September 2017.

Table 12.3: Random intercept multilevel logistic regression of different housing problems' micro-level determinants and housing market structure, 32 countries, 2015

Independent variables	Severe housing deprivation	Overcrowding	Housing cost overburden	Subjective housing cost overburden
Proportion of renters paying reduced rate	−5.0	−7.202*	−2.7	4.924*
Proportion of outright owners	2.915***	4.159***	0.2	1.2
Proportion of those with free rent	−1.5	−6.2	−1.6	10.64***
Proportion of renters paying prevailing prices	1.1	1.3	2.2	−0.1
Intercept	−4.460***	−2.975***	9.704***	2.567***
Log likelihood	−97 258.5	−194 254.4	−140 135.3	−299 765.5
ICC	0.1	0.2	0.1	0.1
N	594 139	593 802	590 167	592 296

Note: All micro-level determinants as in Table 12.2 are included but not shown for reasons of readability.

*, $p < 0.1$; ***, $p < 0.01$.

Source: Authors' computations, UDB September 2017.

Table 12.4: Random intercept multilevel logistic regression of different housing problems micro-level determinants and other macro-level determinants, 32 countries, 2015

Independent variables	Severe housing deprivation	Overcrowding	Housing cost overburden	Subjective housing cost overburden
Total social benefit	−0.101***	−0.122***	0.044**	−0.051**
In-kind benefits	−0.533***	−0.221***	0.059	−0.202***
In cash benefits	−0.559***	−0.722***	−0.01	−0.260**
Adequacy minimum income	−0.032***	−0.044***	0	−0.026***
Mortgage loans in proportion of GDP	−0.030***	−0.039***	0.005	−0.016***
National median disposable income (PPS)	−0.000***	−0.000***	5.60E-06	−0.000***
N	594 139	593 802	590 167	592 529

Note: All micro-level determinants as in Table 12.2 are included but not shown for reasons of readability. Macro determinants are tested one at a time.

**, $p < 0.05$; ***, $p < 0.01$.

Source: Authors' computations, UDB September 2017.

12.6. Conclusions

The situations of the EU Member States are very heterogeneous in terms of housing deprivation, overcrowding or housing cost overburden. These housing problems are more prevalent in eastern and to some extent southern Europe than in western and northern Member States, although with important national nuances.

Our multilevel analysis investigated the role of micro-drivers linked to the composition of the population in terms of social risks, and the role of macro-level differences in terms of structure of the tenure market, level of national income or role of the welfare state.

In terms of micro-drivers, our results confirmed the impact of risk factors related to the household's resources and costs/needs. The results also indicated that most of the household/individual determinants we identified have similar impacts on all the dimensions of housing, with some variations due to the position in the life cycle (age, household type and household size have different impacts on the different aspects of poor housing). However, for the EU indicator of objective housing cost overburden, some risk factors go in the opposite direction compared with the subjective housing cost overburden and the other housing problems analysed. This deserves further investigation regarding the construction and reliability of this indicator.

An important task of this chapter was also to explore if there were specific conditions in the housing market that could explain between-country differences in housing conditions at EU level. Our results confirmed that countries with a higher proportion of outright owners are more likely to suffer from the housing problems under examination than other countries. The proportion of outright ownership is a crude indicator of historical and institutional factors that affect the availability and quality of housing in eastern and southern regimes. In contrast to those of Borg (2015), our results did not confirm that a large integrated rental sector has a protective impact on housing deprivation. This important result sheds new light on previous results. Indeed, once the proportion of outright owners is explicitly included in the model, all the other variables related to the housing market structure are no longer significant.

We were also interested in the role of other measurable macro-determinants. Regarding the impact of welfare regimes, our results indicated that the variable related to in-kind transfers has a protective impact on housing deprivation, as expected. Households that benefit from public services have lower personal costs and higher available incomes for housing consumption. Even though cash social transfers were already taken into account at micro level through the household income, we found a protective impact of benefits in cash. We also highlighted that an adequate minimum income scheme protects people from housing deprivation.

We also tested the impact of the financial market at macro level. The proportion of outstanding residential loans in GDP was negatively associated with housing deprivation, confirming that countries where access to financial markets is extensive suffer from fewer housing problems than others. Our results showed that an important determinant of housing problems is the level of national affluence, even when household-level determinants (e.g. household income) are taken into account. This result, which is also highlighted in Chapter 13 with respect to the determinants of child deprivation, suggests that the national level of affluence serves as a proxy for variables not included in the model, such as household wealth and the quality of public social services.

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Understanding deprivation of children and among couples

13 National risk factors of child deprivation in Europe

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13.1. Introduction

Child poverty has featured on the agenda of the EU for many years. In 2013, a recommendation on 'Investing in children: breaking the cycle of disadvantage' was adopted (European Commission, 2013). It calls on Member States to 'reinforce statistical capacity … where needed and feasible, particularly concerning child deprivation'. The best way to provide accurate information on the actual living conditions of children in the EU, without making assumptions about the sharing of resources within the household, is to develop child-specific deprivation indicators – that is, indicators based on information on the specific situations of children, which may differ from those of their parents. In 2018, the EU made a significant step in this direction by adopting the child-specific deprivation indicator proposed by Guio et al. (2018), using EU-SILC data.

This chapter seeks to gain a comprehensive understanding of the relationship of household-level risk factors (household's labour market attachment, household income, household composition, costs due to needs related to, for example, housing or bad health, etc.) with child deprivation in Europe, using the scale adopted at EU level. Often, the expectation that such social stratification variables are related to deprivation is taken for granted without further argument; this chapter formulates explicit arguments and in particular explains why we expect certain micro-level variables, such as parents' education or migrant status or household QJ, to have a relationship with deprivation, alongside the household's current income.

We also identify the extent to which the impact of household-level risk factors on deprivation varies across European countries. Previous studies have shown that the impact of household-level variables on the AROP risk and the deprivation risk differs across European countries (see Fusco et al., 2011; Verbunt and Guio, 2019). In order to present a tailor-made and robust picture of policy levers that should be used to fight child deprivation in the EU, we present a dual methodological approach to identify such variations in the impact of household-level risk factors on child deprivation.

First, we regress household-level risk factors in a single-level model setting for 31 European countries (27 EU Member States, Iceland, Serbia, Switzerland and the United Kingdom) separately (150). We then go a step further than the usual econometric approach in identifying and comparing significant relationships and their signs across countries. Specifically, we provide additional analysis on a pseudo-explained-variance measure obtained from the separate country-specific single-level regressions. We employ Shapley decompositions on these fit measures, delivering quantified knowledge of how (in)effective the different household-level variables are in explaining child deprivation.

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(150) Norway could not be included because of the large amount of missing data on child deprivation.

As a second method to compare the relative importance of the household-level risk factors across countries, we turn to a multilevel setting in which all countries are pooled together. Multilevel models are often used to study the relationship of country-level independent variables with cross-national variations in the dependent variable ([151]). However, several multilevel deprivation studies have also pointed out that the association of variables at household level with deprivation should not be understood independently from variables at country level (Nelson, 2012; Bárcena-Martín et al., 2014; Visser et al., 2014; Saltkjel and Malmberg-Heimonen, 2017). In this chapter, we exploit the multilevel setting by investigating whether or not the impact of household-level risk factors on deprivation is mitigated by a country's national level of affluence.

The chapter is organised as follows. Section 13.2 defines child deprivation and the new indicators used. Section 13.3 presents the models and estimation strategy. Section 13.4 reviews determinants of child deprivation. Section 13.5 presents the results in detail. Section 13.6 concludes.

13.2. A robust EU measure of child-specific deprivation

The choice of the optimal set of child deprivation items agreed at EU level was driven by both theory and data.

From a theoretical point of view, it largely relies on Townsend's (1979, p. 31) concept of relative deprivation:

> Poverty can be defined objectively and applied consistently only in terms of the concept of relative deprivation. … Individuals, families and groups in the population can be said to be in poverty when they lack the resources to obtain the type of diet, participate in the activities and have the living conditions and amenities which are customary, or at least widely encouraged or approved, in the societies to which they belong. Their resources are so seriously below those commanded by the average individual or family that they are, in effect, excluded from ordinary living patterns, customs or activities.

From a data analysis point of view, the retained items successfully passed statistical tests with regard to their suitability, validity, reliability and additivity (Gordon et al., 2000) ([152]). Guio et al. (2017) also showed a high degree of measurement invariance of these items between countries and socioeconomic groups, which is crucial for modelling child deprivation determinants at European level.

The final list of consists of 12 'children' items and 5 'household' items, which cover both material and social aspects of deprivation:

- children items:

1. some new (not second-hand) clothes,
2. two pairs of properly fitting shoes,
3. fresh fruit and vegetables daily,
4. meat, chicken, fish or vegetarian equivalent daily,
5. books at home suitable for the children's age,
6. outdoor leisure equipment,
7. indoor games,
8. regular leisure activities,
9. celebrations on special occasions,
10. invitation of friends to play and eat from time to time,
11. participation in school trips and school events,
12. holiday;

- household items:

1. replacing worn-out furniture,
2. arrears,
3. access to internet,
4. home adequately warm,
5. access to a car for private use.

([151]) For an overview of multilevel deprivation studies, see Guio et al. (2020).

([152]) On the importance of the reliability of deprivation indicators, see Nájera and Gordon (2019).

The indicator implements an **enforced lack** concept: only children lacking an item for affordability reasons (and not by choice or for any other reasons) are considered deprived of this item. In the analysis presented below, it is important to keep in mind some elements related to data collection and processing. First, EU-SILC data on the living conditions of children are collected not from the children themselves, but from the adult answering the household questionnaire. Second, according to the survey protocol to be followed, if in a given household at least one child does not have an item, it is assumed that all the children belonging to that household lack that item. This is an important caveat in studying within-household differences in deprivation. It would of course be preferable to know the deprivation levels of each child in a household separately; it would then be possible to study differences in child deprivation within individual households, as well as between households (e.g. are girls more likely than boys to suffer from deprivation within a same household, or teenagers more likely than younger children?). Third, for most 'children' items, the information relates to children aged between 1 and 15 (i.e. information about children's items is collected in households with at least one child in this age bracket). Therefore, the child-specific deprivation indicator covers only children aged between 1 and 15. Yet one item is collected in households with at least one child attending school (school trips). Households with children not attending school are considered not deprived in that respect.

Guio et al. (2018) propose a deprivation scale on the basis of an unweighted sum of the 17 items. The reliability of the scale is very high at EU level, as well as in all EU Member States. The main child-specific indicator adopted at EU level is the proportion of children lacking at least three items. In the rest of the chapter, we will analyse the full scale of deprivation (ranging from 0 to 17). This has the advantage of using all the information on the number of deprivations suffered by children, without reducing it to a binary variable. To test the sensitivity of our results to this choice, we also ran national logistic regressions using as dependent variable the deprivation **rate**, with a threshold set at 3+ 'lacks' out of 17, as agreed at EU level. The results and significance of the logit model are usually similar to those of the negative binomial model presented and discussed in this chapter, with the detailed results available from Guio et al. (2020).

13.3. The model and the estimation strategy

The dependent variable ranges from 0 to 17 and displays a large degree of overdispersion, in the sense that the variance is larger than the mean. It is therefore recommended to use a negative binomial model, as this technique weakens the highly restrictive assumption made in the traditional Poisson model that the variance is equal to the mean. Instead, the negative binomial model estimates an additional random parameter that takes the unobserved heterogeneity into account. The estimate of the dispersion parameter is significantly greater than zero in all models, indicating that the dependent variable is indeed overdispersed and that the negative binomial models are the most suitable models.

We run **single-level negative binomial models** to investigate the heterogeneous impact of the household-level variables across countries. The main advantage of estimating single-level models for each country is that it gives a precise estimate of the explanatory power of the model within countries. The overall explanatory power of the household-level model employed is operationalised by the McFadden pseudo-R^2 measure. This measure is based on the likelihood value, and higher values indicate a better fit of the model to the data. We then apply Shapley decompositions on the pseudo-R^2 measure to establish and compare the relative explanatory power of the independent variables (Shapley, 1953). The Shapley approach calculates the exact contribution of each independent variable to the total R^2 value. The method has been used to decompose the goodness-of-fit measure in both linear and logistic regression models (Deutsch and Silber, 2006; Verbunt and Guio, 2019).

We then run **negative binomial multilevel models** using the pooled data set to explain between-country differences in child deprivation. Multilevel models are particularly appropriate to study nested data designs, whereby respondents are organised within more than one level. In our study, individuals are nested within countries. In the present setting, the multilevel models include variables that are not included in the single-level model and that can explain differences in child deprivation between countries. Furthermore, to take into account the fact that the household-level variables can vary across countries, the multilevel model includes, first, a random error term (i.e. random slope) that is added to the coefficient of each household-level variable; second, a cross-level interaction between the household-level variables and GDP per capita. The latter allows the coefficients of the micro-level risk factors to vary with national levels of affluence.

13.4. Determinants of child deprivation

This section provides an overview of the characteristics measured at parents' or household level that would be expected to have a relationship to child deprivation ([153]).

It is well documented that sociodemographic and socioeconomic characteristics of households influence child income poverty and deprivation. Both social stratification – the social stratum to which the household belongs – and resources are at play. The relation between the social stratum and the resources as joint determinants of deprivation is probably much more complex than a reduced form empirical model can account for: the social stratum influences not only the level of resources a household commands, but also their use. To specify an empirical model, notwithstanding this difficulty, we distinguish three sets of household-level variables that can help to explain children's deprivation:

1. long-term command over resources;
2. needs related to health and housing;
3. the size and composition of the household.

Deprivation emerges in the confrontation between available resources and needs. As will become clear, the distinction between variables captured under set 1 and variables grouped under sets 2 and 3 is largely (but not entirely) a distinction between resources and needs. However, important factors that influence both the household's command over resources and its needs are not available in our microdata set. This holds, for instance, for the household's consumption of in-kind benefits, in-kind support from family/friends and a direct measure of wealth.

First, children's material well-being depends on how much the household can consume, which, in turn, depends on its command over resources. Although current (disposable) household income is usually used as a proxy for command over resources, the association between current income and deprivation is far from perfect. This imperfect link is documented extensively in the literature (see, among others, Whelan et al., 2001; Whelan and Maître, 2006, 2007; Berthoud and Bryan, 2011; Fusco et al., 2011; Nolan and Whelan, 2011; Verbunt and Guio, 2019). It can be explained by difficulties in measuring income (as is notably the case for self-employed people) and deprivation, and by the fact that households with equal resources may have different needs and face different costs. But, importantly, it can also be explained by the fact that current income is only one element in a household's command over resources. A household's command over resources is also affected by its previous and future income, its wealth and its ability to borrow.

Alongside current income, we therefore use three variables, available in EU-SILC, which can plausibly serve as proxies for the household's long-term command over resources, its wealth and its ability to overcome short-term financial difficulties: parents' current educational attainment, current household QJ and household members' migrant status. Borrowing from economic jargon, these indicators can be related to the household's permanent income, its wealth and its ability to overcome

([153]) For an extensive review of the micro-level determinants of (material) deprivation, see Perry (2002), Boarini and d'Ercole (2006) and Tárki (2011).

liquidity constraints ([154]). *Ceteris paribus* (for a given level of current income and other household characteristics), a higher level of parents' education can indeed be expected to correlate statistically with (1) a stronger position on the labour market, hence less vulnerability of the household with regard to adverse income shocks (e.g. income shocks because of unemployment or precarious employment); (2) grandparents who were more highly educated and therefore richer, which implies larger bequests to the parents and thus more wealth; (3) easier access to financial institutions to overcome liquidity constraints; (4) for younger parents, a higher future return on human capital. If someone in the household was born outside the EU, this correlates statistically with similar social factors: a more vulnerable position on the labour market, less inherited wealth and more difficult access to financial institutions ([155]). The household QJ is likely to signal a precarious position on the labour market for all working age household members, which is a predictor of their future unemployment risks and, in addition, may hamper access to financial institutions to overcome liquidity constraints. Given its availability in EU-SILC, we are able to add a measure of the household's debt burden, which directly influences its long-term command over resources, in addition to the three proxies just mentioned.

To sum up, in order to proxy as well as possible the long-term command over resources at household level, we use six variables.

1. The yearly (disposable) non-equivalised income of households, expressed in 1 000 PPS (*household income*) ([156]). Both the logarithm and linear forms of the income variable were introduced in the regressions. The best regression fit was obtained with the non-logarithm form of the variable. We use non-equivalised income, because the size and composition of the household enter separately in the regression (see below).
2. The educational attainment of the highest educated parent, operationalised by three dummies: *low education* (no education, primary education or lower secondary education), *medium education* (upper secondary or post-secondary non-tertiary education) and *high education* (tertiary education, used as the reference category).
3. The (quasi-)jobless status of the household (*jobless*), which equals 1 when the adults (aged 18–59, excluding students) have worked less than 20 % of their total work potential during the past year.
4. A dummy measuring if one household member was born outside the EU (*migrant*) ([157]).
5. The debt burden of the household (*debt burden*), which equals 1 if payment of debts from hire purchases or loans other than mortgage or loan connected with the dwelling are considered a heavy financial burden on the household.
6. The presence of self-employed people in the household (*self-employment*), a dummy variable that we include to take into account difficulties in measuring income for this subpopulation.

Second, children living in households with the same resources but different needs may experience very different standards of living. Needs increase the level of resources necessary for a household to maintain its standard of living. Needs notably depend on health, tenure status and the housing situation (see, among others, Whelan et al.,

([154]) The extent to which one needs additional social stratification indicators to gauge an individual's or a household's permanent income, over and above its current income, is a moot question; see Kim et al. (2018) and Brady et al. (2018) for recent explorations of this issue. Here, we start from the theoretical expectation that education, joblessness and migrant status do play a role.

([155]) On the impact of migrant status on (material) deprivation, see de Neubourg et al. (2012).

([156]) The disposable income of a household is obtained by adding up all monetary incomes received from any source by any member of the household or the household itself and then deducting taxes and social contributions paid by the household.

([157]) For the three non-EU countries as of 2018 covered in the chapter (Iceland, Serbia and Switzerland), a child is considered a migrant if at least one member of their household was born in a country that is neither the country of residence nor an EU country.

2004; Fusco et al., 2011; Verbunt and Guio, 2019) ([158]). Therefore, we introduce three variables to proxy the household's needs (and related costs):

1. the adults' self-reported health status variable (*bad health*), which has a value of 1 if at least one adult in the household reports having bad or very bad health ([159]);
2. a tenure dummy (*rent*), which has a value of 1 if the household rents its dwelling on the private market or with a social (free or reduced) tariff, compared with owning its own house ([160]);
3. two housing burden dummies, which measure if households' housing costs, including mortgage repayment (instalment and interest) or rent, insurance and service charges (sewage removal, refuse removal, regular maintenance, repairs and other charges) are a heavy (*heavy housing burden*) or a light housing burden (*light housing burden*), with no housing burden as the category of reference.

Third, we include three sociodemographic variables related to the household size and composition.

1. The total number of dependent children (i.e. all children aged 0–17 and dependent students aged between 18 and 24) in the household (*number of dependent children*), instead of implicitly adjusting the household income for its size and composition with an equivalence scale (as is done for the calculation of income poverty; see Chapter 2 of this volume).
2. The age of the oldest child in the household among those children aged 1–15 (*age of oldest child*), in order to test whether or not the composition of the deprivation basket induces a systematic bias in favour of younger/older children, as will be the case if some of the items are less relevant to some age groups.
3. A dummy indicating that children live in a single-parent household (*single parent*). A priori, this variable can be related both to long-term command over resources and to the needs of the household. From a permanent-income perspective, a single-parent household is more vulnerable: it has fewer opportunities to pool employment risk across adults in the household than households with more than one adult, and is likely to have accumulated less wealth and to have less access to financial institutions to overcome liquidity constraints. From a needs perspective, when non-equivalised household income, the number of children and the housing burden are included in the independent variables, the expectation of the *single parent* variable is more ambiguous. For a given level of non-equivalised household income and number of children, a household with only one adult may be expected to face less cost than a household with more adults (e.g. less food consumption, less transport cost). However, the practical organisation of the household may entail more costs in terms of childcare and domestic services. (Single-parent households may also face more difficulties in reconciling working life and family life and therefore are more likely to opt for part-time employment or inactivity; inactivity or a very low level of activity is, however, already taken into account by the QJ variable.)

These three sets of household-level variables are used in the single-level models. They are complemented by country-level and/or contextual variables in the multilevel model (for the pooled data set).

In the multilevel setting, we are interested in explaining between-country differences in child deprivation. In most of the multilevel models described in the literature, the inclusion of macro-level variables (national social transfers in cash, GDP etc.) is justified by the fact that more generous welfare systems or more prosperous economies lead to lower levels of deprivation. However, once micro-level (household-level) determinants that

([158]) Childcare costs were included in the model (using a proxy based on childcare attendance). However, the variable was missing for a large share of the sample of children and had no significant impact on child deprivation for the rest of the sample. A variable on childcare cost burden was collected in the EU-SILC ad hoc module on public services in 2016, and should be more appropriate to test the impact of childcare costs on child deprivation when it becomes available.
([159]) We tested 'limitation in daily activity' and 'suffering from a chronic condition' as alternatives for the bad health variable. The bad health specification had the best fit with the data.
([160]) We introduced separate dummies for private market renting, renting with a free or reduced tariff and owning a house with a mortgage. The coefficients of the market and social renting gave very similar results, while owning a house with a mortgage was insignificant.

capture individual resources and social transfers received by the household are included in the model, the reason why macro-level variables related to GDP or aggregated social transfers would still have a significant relationship with deprivation is generally not discussed. A priori, one would not expect that macro-drivers that are strongly related to variables included at micro level should significantly explain between-country differences in child deprivation in the multilevel model. To further investigate this question, we included in the model four macro variables: GDP per capita, two variables related to social transfers, and the level of unemployment. These variables are defined as follows.

1. GDP per capita, expressed in 1 000 PPS (*GDP per capita*).
2. The generosity of social transfers, as measured by the share of total (in-kind and in-cash) social spending as a percentage of GDP. This variable is derived from the Eurostat ESSPROS database (total social benefits, % of GDP). Social spending covers sickness/healthcare, disability, family/children, unemployment, pension, survivor, housing and all social exclusion benefits not elsewhere classified.
3. The pro-poorness of cash social benefits, as measured as the degree of targeting by the share of transfers that is distributed to the lowest five deciles of the pre-transfer household income distribution of children (*pro-poorness bottom 50*).
4. The unemployment rate, the number of people unemployed (as defined by the International Labour Office) as a percentage of the active population; it is derived from the Eurostat database (*unemployment rate*). Even though we control for low work intensity at household level (see above), we also introduced this variable to account for the possible effect of the business cycle on the size and pro-poorness of social benefits.

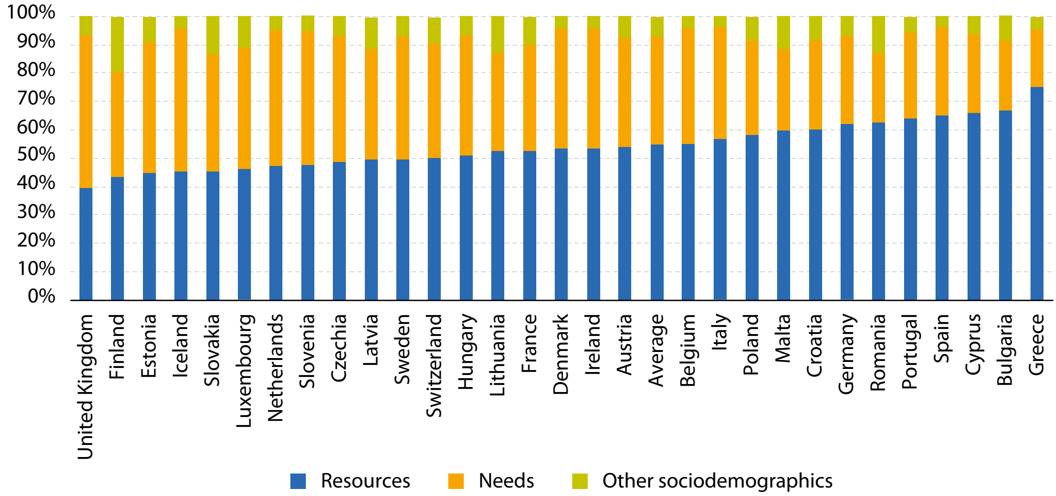
13.5. The results

13.5.1. Single-level models

We ran negative binomial models at country level. We calculated pseudo-R^2 measures to assess the overall explanatory power of the models employed. Table 13.1 reveals considerable between-country variation in the McFadden pseudo-R^2 measure (see second column). This means that the explanatory power of the household-level variables differs strongly between countries, which is a first interesting result. The model is the most powerful in explaining child deprivation in the countries with the lowest shares of child deprivation (Belgium, Denmark, the Netherlands, Austria and Sweden). Conversely, the countries where the single-level model has a lower explanatory power are Bulgaria, Estonia, Italy, Cyprus, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Serbia and Slovakia, all with relatively high child deprivation levels. Yet the specific situations of Greece and Hungary should be stressed: these countries have very high levels of child deprivation, but their R^2 values are at the level of the weighted average of the 31 countries (Hungary) or higher (Greece). In countries where the single-level model has a lower explanatory power, differences in socioeconomic characteristics of households play a (much) smaller role in explaining the number of deprivations suffered by children. In several of these countries, this may be because the general standard of living is low and all children have, as a consequence, a greater likelihood of being (more) deprived.

In terms of relative shares of explanatory power of the determinants of child deprivation, Table 13.1 and Figure 13.1 show that the group of variables related to resources (income, presence of self-employed people in the household, education, QJ, debt burden and migration) make, on average, a relative contribution of 55 % to the fit. The variables related to needs (housing cost burden, bad health and tenure status – 'rent' variable) represent 38 %. The other sociodemographic variables (household structure and size) contribute around 7 %. Figure 13.1 clearly illustrates that the explanatory power of the different variables differs between countries. In the richest countries, the explanatory power of the variables related to needs is larger. In countries with the highest rates of child deprivation, the explanatory power of resources variables is generally greater.

Figure 13.1: Relative share of different household-level variables in the Shapley decompositions of the pseudo-R^2 measures by country, 2014
(%)



Note: 'Resources' refers to income, self-employment, low and medium education, QJ, debt burden and migration; 'Needs' to light and heavy housing cost burden, rent and bad health; 'Other sociodemographics' to household structure and size. Countries are ranked according to the relative share of the variables related to the household resources in the Shapley decomposition.

Reading note: In Greece, the group of variables related to resources make a relative contribution of more than 70 % to the fit.

Source: Authors' computations, UDB September 2016.

The relationship of individual household income to child deprivation is significant in all 31 countries (see Table 13.2 for the detailed results). With an average contribution of 25 % to the fit (from 7 % in Slovakia to 36 % in Cyprus, 37 % in Portugal and 50 % in Greece; see Table 13.1), it is the most important variable related to resources.

The educational level of the parents is also strongly associated with child deprivation, even when income, labour market attachment and other household-related demographic differences are taken into account. This confirms our expectation that educational attainment is a good proxy for long-term command over resources, independently of other proxies of command over resources. It makes an average contribution of 15 % to the fit and is the third most important variable across the data set (after income and housing cost burden). The education variables are significant in all models tested and in all countries (with the exceptions of lower education in Sweden, and medium education in Denmark and Luxembourg). The association is strongest in Bulgaria, Hungary and Romania (27–37 %) as well as, to a much lesser extent, Poland, Lithuania, Slovakia, Portugal and Malta (20–22 %). These are all countries with (very) high child deprivation levels. A plausible explanation for this diverging effect across countries, which does not contradict our theoretical expectation, is that higher education is more scarce in these countries and thus more valuable on the labour market.

Living in a household suffering from QJ is positively related with child deprivation in the majority of countries, even when household income is controlled for (for similar results see also Fusco et al., 2011; de Graaf-Zijl and Nolan, 2011). The variable is, however, not significant in Austria, Czechia, Denmark, Hungary, Iceland, Lithuania, Luxembourg, the Netherlands and Poland (Table 13.2). The contribution of QJ to the fit, as shown in Table 13.2, is higher than 10 % in Ireland, Spain, Croatia, Malta, Slovakia and Serbia. The average contribution is 7 %.

For similar income levels, households with at least one self-employed member tend to suffer from a lower number of deprivations: in 22 countries (out of 31) the coefficient is significant and negative. In the remaining countries it is also negative but non-significant, except for Switzerland, where the coefficient is positive and high (0.39). This confirms previous results (see also Fusco et al., 2011; Berthoud and Bryan, 2011) and may be partly explained by the difficulty of measuring self-employment income in surveys such as EU-SILC or by the challenge of discriminating between personal and professional assets and costs for the self-employed. Migration has the largest relative contribution to the fit measures in Denmark, Sweden and Switzerland: 7–12 %, in contrast to 3 % for the average. Households with a high debt burden also have a higher deprivation risk (this explains 5 % of the fit, on average, across the 31 countries analysed). The share of the fit is highest (10–15 %) in the richest countries such as Denmark, Iceland, Sweden and Switzerland.

As expected, households with higher costs face a higher child deprivation risk. The variable related to the housing burden appears to have a strong association with child deprivation in most countries: it explains more than 20 % of the fit in almost all countries and as much as 43 % in Slovenia, with an average of 25 %. Children living in households renting their dwellings tend to suffer more from deprivation than those owning them in all countries, except in Bulgaria, Estonia, Romania, Serbia and Slovakia, where the difference by tenure status is not significant. This variable explains a large share of the fit in Austria, Belgium, Denmark, Germany, Luxembourg, the Netherlands, Sweden, Switzerland (10–18 %) and the United Kingdom (26 %). The average relative contribution to the pseudo-R^2 measure is 7 %.

Households in which at least one adult suffers from health problems also face higher risks of child deprivation (except in Bulgaria and Lithuania), which is in line with results shown in other studies (Fusco et al., 2011). This is explained by the burden of additional healthcare costs of having a household member with (very) bad health. It would be interesting to include information on any child health problems in the model. This variable, not yet available in EU-SILC, will be collected in future modules on child deprivation and living conditions.

Among the sociodemographic variables included in the model, the number of children is positively related to child deprivation in all countries. The results also confirm that living in a single-parent household increases the risk of child deprivation in many countries (22 out of 31). Given that we use a non-standardised measure of household income, this is a salient result: even if only one adult is dependent on the household's income, rather than two adults, the risk of deprivation increases. In the countries where this is not the case, this can be interpreted as meaning that living in a single-parent household does not per se increase the child deprivation, but the associated characteristics of these households do, in terms of low income and low labour market attachment.

The age of the oldest child has no significant relationship with the child deprivation risk in two thirds of the countries studied. This is an important result, as it indirectly confirms that the composition of the 17 deprivation-item basket proposed by Guio et al. (2018) does not lead to systematic differences between age groups.

13.5.2. Multilevel model and cross-level interactions

In this section, we pool all countries together and add a multilevel structure to investigate the between-country differences in child deprivation across the 31 countries analysed.

Interestingly, the results in Table 13.3 show that GDP per capita is an important predictor of child deprivation (coefficient of −0.39). As explained in Section 13.4**,** the fact that GDP per capita has a negative association with child deprivation, when individual household income and other micro-drivers are controlled for, is not expected a priori. To explain this result, we argue, in contrast to most of the previous literature, that the association between GDP and child deprivation is not explained by the impact of the level of affluence on child deprivation (as this is taken into account in the model by the level of household income), but is because GDP provides proxies for contextual elements not included in the model, We propose

Table 13.1: Shapley decompositions of the household-level variables on the pseudo-R^2 measure by country, 2014
(%, rank in brackets)

Country	R^2	Resources					Needs			Other sociodemographics
		Income	Education	Quasi-joblessness	Debt burden	Migrant	Housing burden	Bad health	Rent	Household structure
Belgium	0.23	28.2 (1)	11.8 (4)	8.4 (5)	4.5 (6)	2.3 (9)	21.2 (2)	4 (8)	15.7 (3)	4 (7)
Bulgaria	0.07	22.2 (2)	37.3 (1)	6.4 (5)	0.8 (8)	0.1 (9)	22 (3)	1.7 (6)	0.8 (7)	8.7 (4)
Czechia	0.20	20.5 (2)	16.2 (3)	8 (5)	3.8 (8)	0.1 (9)	31.8 (1)	4.1 (7)	8.8 (4)	6.7 (6)
Denmark	0.24	25.2 (1)	4 (7)	3.9 (8)	11.9 (4)	8.7 (5)	25.1 (2)	3 (9)	14 (3)	4.3 (6)
Germany	0.18	31.5 (1)	15.5 (3)	9.1 (5)	5.4 (7)	0.7 (9)	16.7 (2)	4.7 (8)	10 (4)	6.4 (6)
Estonia	0.14	19.3 (2)	11.1 (3)	9.5 (4)	3.9 (6)	1.1 (8)	42.3 (1)	2.9 (7)	1.1 (9)	8.7 (5)
Ireland	0.18	28.4 (2)	8.8 (4)	11.9 (3)	4.3 (6)	0.3 (9)	30.5 (1)	3.9 (8)	7.6 (5)	4.3 (7)
Greece	0.19	50.3 (1)	13.1 (3)	6 (4)	1.3 (9)	4.3 (6)	16.1 (2)	2.8 (7)	1.4 (8)	4.6 (5)
Spain	0.20	29 (1)	17.2 (3)	10.6 (4)	3.7 (7)	4.6 (5)	25.5 (2)	1.7 (9)	4.2 (6)	3.5 (8)
France	0.17	23.7 (2)	15.3 (3)	5 (6)	3.9 (8)	4.6 (7)	25.9 (1)	2.9 (9)	8.6 (5)	10 (4)
Croatia	0.15	26.9 (1)	18.8 (3)	12.8 (4)	1.9 (8)	1.5 (9)	21.6 (2)	5.4 (6)	2 (7)	8.9 (5)
Italy	0.14	26.8 (2)	15.6 (3)	5.3 (5)	4.3 (7)	4.8 (6)	30.1 (1)	2.7 (9)	6.7 (4)	3.7 (8)
Cyprus	0.13	35.6 (1)	16.2 (3)	5.6 (6)	6.7 (4)	1.9 (9)	20.9 (2)	3.4 (8)	3.5 (7)	6.2 (5)
Latvia	0.14	25 (2)	15.8 (3)	4.8 (5)	3.8 (6)	0.1 (9)	34.3 (1)	2.1 (8)	2.8 (7)	11.2 (4)
Lithuania	0.14	23.5 (2)	21.3 (3)	4 (5)	1.8 (7)	1.9 (6)	32.3 (1)	1.1 (9)	1.2 (8)	13.1 (4)
Luxembourg	0.20	22.8 (2)	9.9 (5)	1.8 (9)	8.4 (6)	3.6 (8)	24.7 (1)	3.8 (7)	13.9 (3)	11.1 (4)
Hungary	0.17	18.6 (3)	27.4 (2)	3.8 (5)	1 (8)	0.1 (9)	37.3 (1)	2.8 (6)	2.3 (7)	6.7 (4)
Malta	0.15	20.1 (2)	19.7 (3)	11.6 (4)	8.3 (6)	0.2 (9)	21.7 (1)	2.1 (8)	4.9 (7)	11.4 (5)
Netherlands	0.25	22.3 (2)	8.4 (4)	5.1 (6)	6.8 (5)	4.5 (8)	29.3 (1)	2.3 (9)	16.7 (3)	4.7 (7)
Austria	0.23	17.4 (3)	17.6 (2)	4 (8)	8.9 (5)	6 (7)	22.6 (1)	4 (9)	12.1 (4)	7.4 (6)
Poland	0.13	29.6 (1)	22.3 (3)	3.2 (6)	3 (7)	0.3 (9)	24.9 (2)	3 (8)	5.1 (5)	8.5 (4)
Portugal	0.17	37.2 (1)	19.8 (3)	5.1 (6)	1.6 (8)	0.3 (9)	21.8 (2)	2.6 (7)	5.8 (4)	5.7 (5)
Romania	0.09	30.1 (1)	26.8 (2)	2.8 (5)	2.7 (6)	0.3 (9)	22.4 (3)	2 (7)	0.3 (8)	12.6 (4)
Slovenia	0.17	16.9 (2)	16.3 (3)	3.9 (6)	7 (4)	3.5 (7)	43.3 (1)	1.8 (9)	2.4 (8)	4.9 (5)
Slovakia	0.14	7.2 (5)	20 (2)	13.3 (4)	4.6 (6)	0.2 (9)	37.1 (1)	1.5 (8)	2.6 (7)	13.6 (3)
Finland	0.17	18.3 (3)	7.7 (5)	8.9 (4)	6.5 (7)	2.1 (8)	29.6 (1)	0.6 (9)	6.6 (6)	19.6 (2)
Sweden	0.28	13.6 (4)	4 (8)	6.5 (7)	14 (3)	11.8 (5)	21.5 (1)	3.2 (9)	18.2 (2)	7.2 (6)
United Kingdom	0.19	15 (3)	7.9 (5)	8.7 (4)	7.5 (6)	0.7 (9)	23.7 (2)	3.8 (8)	26.3 (1)	6.4 (7)
Iceland	0.16	14.4 (4)	12.2 (5)	3.2 (8)	15.1 (3)	0.3 (9)	29.2 (1)	16 (2)	5.3 (6)	4.3 (7)
Serbia	0.13	31.9 (1)	17.1 (3)	10.9 (4)	0.5 (7)	0.1 (9)	23.9 (2)	7.2 (6)	0.3 (8)	8.2 (5)
Switzerland	0.20	18.4 (2)	9 (6)	5.6 (8)	9.9 (4)	7.1 (7)	21.3 (1)	1.4 (9)	17.7 (3)	9.5 (5)
Average	0.17	25.3 (1)	15.3 (3)	6.9 (6)	4.9 (7)	2.7 (9)	24.7 (2)	3.1 (8)	10 (4)	7 (5)

Note: The income column includes the relative contribution of the household disposable income variable and the self-employment dummy. For Croatia, the 'light housing burden' variable has been dropped, as the Shapley decomposition model did not converge when this variable was included.
Reading note: The R^2 captures the relative fit of the (full) model to the data. The percentages reflect the relative contribution to the fit, and the number between brackets ranks the variables according to their respective relative contribution. In Belgium, the contribution of household income to the fit reaches 28 %. This is the variable that contributes the most to the fit.
Source: Authors' computations, UDB September 2016.

Table 13.2: Negative binomial single-level models by country, 2014

Country	Intercept	Resources							Needs				Other sociodemographics		
		Household income	Low education	Medium education	(Quasi-) joblessness	Self-employment	Debt burden	Migrant	Heavy housing burden	Light housing burden	Bad health	Rent	Number of dependent children	Single parent	Age of oldest child
Belgium	-0.2934	-0.0001***	0.5582***	0.3364***	0.2649***	-0.5986***	0.5497***	0.0046	1.5538***	0.7538***	0.3504***	0.7013***	0.029	0.2258***	-0.0142
Bulgaria	0.9403***	-0.0001***	0.7345***	0.3395***	0.1331**	-0.1736***	0.1375**	-0.0922	0.7595***	0.3546**	0.0801	0.0005	0.0041	0.1158	0.0244***
Czechia	-0.5801**	-0.0002***	0.9064***	0.5112***	0.086	-0.2469***	0.3204***	0.3518*	1.5299***	0.6606***	0.3321***	0.3648***	0.0811***	0.1972***	-0.0107*
Denmark	-1.2799***	-0.0001***	0.5404***	0.0504	-0.1335	-0.5449***	1.1392***	0.7624***	1.6162***	1.1928***	0.4008**	0.9339***	-0.0626	0.2154	0.0253*
Germany	-0.9912***	-0.0001***	0.9486***	0.5119***	0.6238***	-0.2738*	0.5777***	0.1995**	1.2815***	0.5561***	0.5807***	0.5677***	0.0833**	0.3078***	-0.0049
Estonia	-1.382***	-0.0001***	0.5481***	0.2768***	0.5406***	-0.4163***	0.419***	0.1699**	1.9254***	1.0666***	0.237***	-0.07	0.0353	0.3684***	0.0265***
Ireland	-0.6408***	-0.0002***	0.339***	0.1798***	0.2373***	-0.3254***	0.2902***	0.0049	1.9681***	1.2807***	0.5288***	0.2791***	-0.0233	0.1112***	-0.0017
Greece	0.8189***	-0.0001***	0.3755***	0.1781***	0.1048***	-0.0939***	0.0964***	0.1776***	0.9293***	0.5203**	0.2981***	0.1081***	0.0472***	0.1338**	0.0028
Spain	-0.5108**	-0.0001***	0.5756***	0.3957***	0.442***	-0.1505***	0.448***	0.3259***	1.2697***	0.1664	0.2251***	0.24***	0.0467***	0.066	0.0076**
France	-0.5168***	-0.0001***	0.6332***	0.3905***	0.2235***	0.01	0.3781***	0.3299***	1.164***	0.71***	0.3098***	0.344***	0.089***	0.2667***	0.0096*
Croatia	-23.6173***	-0.0002***	0.9207***	0.4176***	0.4551***	-0.1635*	0.2218***	0.1625**	24.0614***	23.1233	0.3335***	0.3527***	0.0939***	-0.163	0.0044
Italy	0.1116	-0.0001***	0.6864***	0.2191***	0.2158***	-0.2077***	0.4973***	0.3809***	0.6938***	-0.4688**	0.4857***	0.3692***	0.0746***	-0.0158	0.0035
Cyprus	0.0202	-0.0001***	0.3697***	0.1677***	0.1899***	-0.034	0.2848***	0.1525***	1.2895***	0.4985***	0.3278***	0.1542***	-0.0106	0.3755***	0.0135***
Latvia	-0.1542	-0.0001***	0.6017***	0.2827***	0.1481**	-0.2177***	0.2731***	0.1007	1.3495***	0.7091***	0.1841***	0.1223***	0.1118***	0.0906	0.0144***
Lithuania	-0.9646***	-0.0001***	0.8792***	0.4643***	0.0714	-0.4225***	0.2672***	0.4799***	1.7587***	1.133***	0.0943	0.1708**	0.13***	0.1155	0.0042
Luxembourg	-1.7437***	-0.0001***	0.3623***	0.1219	-0.1286	-0.3858*	0.6929***	0.4037***	1.5178***	0.5754**	0.5629***	0.6549***	0.009	0.8042***	0.0058
Hungary	-0.5097***	-0.0002***	1.0159***	0.5985***	-0.0212	-0.6102***	0.1136***	-0.1384	2.0151***	1.2331***	0.1543***	0.25***	0.0404***	0.2127***	-0.0017
Malta	-0.4359*	-0.0001***	0.5236***	0.1848**	0.3472***	-0.1432*	0.636***	0.1987***	1.0945***	0.4071**	0.5662***	0.1504**	0.1435***	0.266***	-0.0034
Netherlands	-0.8299***	-0.0001***	0.5395***	0.2234***	0.0587	-0.0355	0.7384***	0.5932***	1.7179***	1.0258***	0.6247***	0.7235***	-0.0492*	0.4331***	-0.0082
Austria	-1.52***	-0.0001***	1.1523***	0.5769***	0.1478	-0.4813***	0.9784***	0.2211***	1.4519***	0.668***	0.3637***	0.6205***	0.066*	0.2845***	0.0051
Poland	-0.3773**	-0.0002***	1.0793***	0.6337***	0.076	-0.4437***	0.3795***	0.6914***	0.9752***	0.0262	0.2113***	0.3569***	0.1073***	0.3239***	0.0037
Portugal	0.261*	-0.0001***	0.5541***	0.2571***	0.1008**	-0.4336***	0.1884***	0.1799***	1.1159***	0.5653***	0.1639***	0.183***	0.0268	0.0312	0.0091**
Romania	1.1457***	-0.0003***	0.5131***	0.3385***	0.1211*	-0.0396	0.2779***	-15.2373	0.7842***	0.3786***	0.1684***	0.0965	0.0486***	0.3355***	0.0059
Slovenia	-1.1679***	-0.0001***	0.7046***	0.3442***	0.1563**	-0.2937***	0.437***	0.2404***	1.8831***	0.8745***	0.4594***	0.1622***	0.1164***	0.1743**	-0.0024
Slovakia	-1.5961***	-0.0001***	0.8941***	0.4741***	0.552***	-0.2366***	0.206***	1.2629	2.02***	1.0698***	0.2235***	0.2067***	0.1554***	0.2993**	0.0071
Finland	-1.4217***	-0.0001***	0.5983***	0.2891***	0.6315***	-0.1197*	0.5583***	0.4719***	1.5859***	0.828***	0.3424**	0.4078***	0.0927***	0.2259***	0.0004
Sweden	-2.6208***	-0.0001***	0.0472	0.4236***	0.6224***	-0.3495*	1.3778***	0.804***	1.6201***	1.1335***	0.7127***	0.8543***	0.0747*	0.2699*	0.0226
United Kingdom	-0.9145***	-0.0001***	0.3394***	0.1905***	0.2885***	-0.0731	0.3892***	0.0976**	1.0651***	0.4919***	0.4128***	0.8403***	-0.0141	0.1425***	0.0153***
Iceland	-0.5677**	-0.0001***	0.5673***	0.2272***	0.0616	-0.0887	0.5411***	-0.2607*	1.067***	0.326**	1.0468***	0.2701***	-0.0149	0.0038	0.014
Serbia	0.4812*	-0.0003***	0.6203***	0.2509***	0.2514***	-0.3455***	0.1104***	-0.0064	0.6683***	-0.1271	0.2625***	0.1341***	0.0394***	0.141**	0.0165***
Switzerland	-2.8659***	-0.0001***	0.5984***	0.3126***	0.902***	0.3948**	0.7305***	0.55***	1.7356***	0.9975***	0.3889*	0.926***	0.1328***	0.7218***	-0.0001

Note: * significant at 10 % level; **, significant at 5 % level; ***, significant at 1 % level.

Reading note: Household income decreases the number of deprivations in all countries (this result is significant at 1 % level in all countries).

Source: Authors' computations, UDB September 2016.

some plausible candidates for these contextual elements in the conclusion.

As expected, all other country-level variables (i.e. social spending generosity, pro-poorness of social benefits, unemployment rate) have statistically insignificant relationships to child deprivation when household income and GDP are co-regressed. In Guio et al. (2020) we showed that the impact of social transfers in cash operates mainly through household income (i.e. aggregated cash transfer levels are only significant when household income is omitted from the model). This should not lead to the conclusion that cash transfers are unrelated to child deprivation; what our model shows is, quite logically, that cash transfers do not have an association independently from the distribution of household income at micro level.

Table 13.3 also examines the varying impacts of the household-level variables by adding a country-specific random error term to the coefficients of the household-level variables and by introducing a series of cross-level interactions between GDP per capita and the household-level variables. The random error terms ensure that the coefficients of the cross-level interactions with GDP per capita are not influenced by other effects. The results are given in the second and third columns of Table 13.3. All random slopes, with the exception of the age of the oldest child, are statistically different from zero (last column) ([161]). This confirms our findings from the single-level analysis that the relationship of the household-level variables to child deprivation differs across countries. The results of our cross-level interactions give a more nuanced picture. Specifically, we find that GDP per capita levels mitigate the impact of the household-level variables that relate to households' resources, while they increase the impact of variables that capture households' needs.

The impact of variables that capture or directly influence households' permanent income becomes smaller as a country's GDP per capita increases, except for variables related to debt burden and migration background. Indeed, the positive cross-level interaction between GDP per capita and household income indicates that **the negative association of household income becomes smaller when GDP per capita increases**. So household income has a larger effect in less affluent countries. In addition, the negative cross-level interaction between the low and medium education dummies and GDP per capita indicates that the negative impact of low education on child deprivation is smaller in the most affluent countries, that is, children in **low-educated households are better protected from deprivation in the more affluent countries**. Whelan and Maître (2012) already showed for the whole population that lacking educational qualifications has a more negative relationship to deprivation as GDP declines. However, in contrast to their results, in our model the interaction effects do not explain away the impact of GDP per capita as an independent variable (which remains significant when interaction terms are included). These results imply that the variables in our model that aim to capture households' command over resources have a relatively stronger association with child deprivation in countries with a low standard of living than in countries with a high standard of living. Finally, while the coefficient of QJ varies across countries (i.e. the random slope is significant), it does not depend on GDP per capita.

The results further indicate that the **deprivation-increasing (i.e. statistically positive) effect of variables related to household needs** (e.g. having a heavy housing cost burden, renting one's dwelling or having at least one household member struggling with bad health) **increases as GDP per capita increases**. The cross-level interaction with the light housing burden dummy is positive, but not significant. These results confirm the single-level analysis, in which variables that measure household needs/costs contribute more to the fit in richer countries.

The coefficient of being a single parent or having someone in the household with a migrant background is larger in the more affluent countries. The cross-level interaction between GDP per capita and the number of children living in the household and the age of the oldest child is insignificant.

([161]) The covariance between the random intercepts and the random slopes was not estimated for computational reasons. We also conducted a robustness check of a model that does not include random slopes. The results indicate that none of the significant cross-level interactions lose their significance or change sign. Two insignificant relationships (i.e. slight housing burden, number of children) become significant once the random slopes are dropped.

Table 13.3: Cross-level interaction negative binomial multilevel model, pooled data set, 2014

Independent variables	Base coefficient	Interaction with GDP per capita	Random slope
Household-level variables			
Household income	−0.04***	0.003**	0.00008***
Self-employment	−0.21***	0.003	0.02***
QJ	0.25***	0.02	0.03***
Low education	0.94***	−0.08**	0.04***
Medium education	0.53***	−0.05**	0.01***
Debt burden	0.1	0.13***	0.04***
Bad health	0.18***	0.07***	0.01**
Heavy housing burden	1.18***	0.1**	0.06***
Light housing burden	0.49***	0.08	0.06***
Rent	−0.08	0.16***	0.04***
Number of dependent children	0.11***	0.01	0***
Single parent	−0.1	0.07***	0.01**
Age of oldest child	0.01***	−0.0004	0.00002
Migrant	0.12	0.06*	0.04***
Constant	0.37		0.28***
Country-level variables			
GDP per capita	−0.39***		
Unemployment rate	0.03		
Total social benefits (% of GDP)	−0.02		
Pro-poorness (bottom 50)	0		
Model information			
Over-dispersion parameter	0.55***		
N of observations	88 901		

Note: * significant at 10 % level; **, significant at 5 % level; ***, significant at 1 % level.

Reading note: Column 2 gives the coefficients of the cross-level interactions between GDP per capita (in 1 000 PPS) and the household-level variables. For example, the coefficient of the bad health dummy in Belgium is 2.49 = 0.18 + 0.07 × 33, where 0.18 is the base effect, 0.07 is the coefficient of the cross-level interaction and 33 refers to the GDP per capita level of Belgium (in 1 000 PPS). Column 3 gives the estimates of the variance in the random slope for each household-level variable. A higher variance implies a stronger variation in the coefficients of the household-level variables between countries.

Source: Authors' computations, UDB September 2016.

13.6. Conclusion

Our analyses confirm the combined relationship of variables related to long-term command over resources (current household income, parents' education, household labour market attachment, burden of debts, migration status) and variables indicating household needs (costs related to housing, tenure status and bad health) to child deprivation.

The household-level risk factors were the most effective in explaining child deprivation in countries with the lowest levels of child deprivation (Belgium, Denmark, the Netherlands, Austria and Sweden). Conversely, the countries where the single-level model has a lower explanatory power are Bulgaria, Estonia, Italy, Cyprus, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Serbia and Slovakia. In these countries the general standard of living is lower and children are more likely to be deprived.

The three most powerful predictors of child deprivation are housing cost burden, household income and educational level of parents. However, our results also clearly illustrate that the explanatory power of the different household-level variables differs across countries. In the richest countries, the explanatory power of the variables related to household needs is the largest, whereas, in the countries with the highest child deprivation, the explanatory power of resources is generally greater (with the exception of debt and migration). This means that countries differ in terms of the association of each variable with the child deprivation risk; that is, household income, QJ and housing cost burden do not have the same relationship with child deprivation across countries. Our results highlight that the age of the oldest child has no significant relationship to child deprivation in two thirds of the countries studied. This is an important result, as it indirectly confirms that the composition of the deprivation basket does not lead to systematic differences between age groups.

Cross-effects in the multilevel model also indicate that the impact of certain individual risk factors is mitigated by countries' levels of affluence. We find that GDP per capita levels mitigate the impact of household-level variables that relate to households' long-term command over resources (except for debt and migration status, which we see as components of that long-term command over resources), while they increase the impact of variables that capture households' needs. These results confirm the findings from the single-level analysis and illustrate the importance of looking at national drivers of child deprivation. However, in contrast to Whelan and Maître (2012), in our model the interaction effects do not explain away the impact of GDP per capita as a significant independent variable.

The fact that GDP per capita plays a role in explaining child deprivation, after including cross-level interactions (capturing the mitigating impact of GDP per capita on the household-level risk factors), household income (capturing differences in living standards between countries) and variables capturing the size and the pro-poorness of the welfare state (which are known to be correlated with GDP per capita), is somehow surprising. Why does a country's level of affluence, the full impact of which is already taken into account at household level, directly through household income and indirectly through the cross-level interactions, have additional explanatory power when aggregated at country level? This result is not expected a priori.

It seems that GDP per capita correlates with 'hidden' contextual factors, which were not included in our data set, such as the average household wealth and the size of gifts between households. One may also conjecture (although this hypothesis would need further examination) that richer countries have features that lead to less volatility of incomes, notably within the working-age population and at the bottom end of the income distribution: a larger public sector and better-functioning automatic stabilisers in their welfare edifice reduce this volatility. In other words, it seems plausible to argue that these contextual variables increase households' permanent income, notably within the working-age population and at the bottom end of the income distribution, and therefore reduce child deprivation. Another possible reason might be that GDP per capita is a proxy for qualitative differences, such as the effectiveness of public support, notably the quality of public social services. Richer countries can be expected to provide public services of better quality (education, childcare, public transport systems, etc.), which should increase permanent income and/or decrease household needs and related costs in the most effective way. Finally, it may also be the case that the notion of affordability changes with the average level of incomes. We believe this result deserves more elaboration and interpretation. We leave it as an interesting avenue for further research.

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14 Deprivation among couples: sharing or unequal division?

Anne-Catherine Guio and Karel Van den Bosch [162]

14.1. Introduction

In standard poverty and deprivation analyses, all household members are assumed to share equal living conditions. This assumption is, for example, implicit in the AROP rate used at EU level, which is derived from household income. The same assumption has also been made to date for the EU SMD indicator used in the social inclusion target, which is based on nine items collected in the household questionnaire (see Chapter 1 for a definition). Researchers have been aware for some time that this assumption is rather restrictive (Jenkins, 1991), and could result in a downward bias of estimates of the extent of poverty and deprivation, especially among some subgroups, such as women and children. Intra-household inequality could mean that some persons in a household are living in poverty or deprivation, even though the household as a whole is above the threshold, and also that a family below the poverty threshold could contain someone who is above it.

When looking into the 'black box' of intra-household distribution, it is important to distinguish between outcomes and processes. The first term covers consumption, living standards, deprivation and, ultimately, well-being, whereas the second concept refers to financial control, resource management, income pooling and spending of resources within households (Jenkins, 1991; Bennett, 2013). A number of studies, using various methods and data, have looked into the intra-household distribution of incomes and consumption. Although a few have studied the distribution between parents and children (see for example Main and Bradshaw, 2016; Bárcena Martín et al., 2017), most studies focus on the intra-couple distribution (as we will do below), covering different aspects. Some investigate the ways in which a couple's finances are managed and controlled, while others have studied the individual consumption or living standards of wives and husbands within couples (see Bennett, 2013, for a review). Some economists have tried to derive the 'sharing rule', that is, the resource shares of each individual in a household, from data on household consumption and labour supply (e.g. Cherchye et al., 2015). Only a few studies, of Ireland (Cantillon and Nolan, 1998, 2001; Cantillon et al., 2015), have looked at differences in deprivation within couples. These studies initiated and used Irish survey (1987) data that contain items of deprivation at both household and individual levels. These items are similar to those recently agreed at EU level to be included in the revised measure of material and social deprivation (see Chapter 1 above). These studies indicate that differences within couples are not very common, but that when they do occur they are more often to the disadvantage of wives than of husbands.

This chapter presents empirical evidence at EU level on this issue using a number of items on deprivation collected at individual level. It maps the extent of intra-couple inequality in deprivation,

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and analyses its determinants. It is structured as follows. The next section presents definitions and data. Descriptive results are shown in Section 14.3. Section 14.4 investigates the determinants of the gender deprivation gap. Section 14.5 concludes, discussing the substantive findings and making recommendations for future data collection.

14.2. Definitions and measurement

In 2009, the EU countries and the European Commission adopted deprivation indicators (Guio, 2009). These indicators are widely used by EU countries and the Commission to monitor progress in the fight against poverty and social exclusion at national and EU levels in the context of EU co-operation in the social field, as exemplified by the inclusion of SMD in the headline indicator of the Europe 2020 strategy target on the AROPE risk. The deprivation indicators were revised, as they were based on a small number of items (nine items), of which three appeared to fail the robustness tests performed by Guio et al. (2012, 2017). In contrast to its predecessor, the revised EU MSD indicator may capture intra-household differences between adults living together. Indeed, among the 13 items that passed the robustness analysis and were chosen to be included in the revised EU MSD indicator (see Chapter 1 above and Guio et al., 2017), six items are collected at adult level (for all persons aged over 15 years).

In this chapter, we will focus on these adult items to better understand the extent of intra-couple inequality. These items measure the inability of a person to:

- replace worn-out clothes with new ones;
- have two pairs of properly fitting shoes;
- spend a small amount of money each week on oneself;
- have regular leisure activities;
- get together with friends/family for a drink/meal at least monthly;
- have an internet connection.

The information on adult deprivation is collected using a question with three answer categories:

Can you tell me if:

- you have the item?;
- you do not have the item because you cannot afford it?
- you do not have the item for any other reason?

The analysis is limited to married and cohabiting couples. Since we are interested in differences between women and men, the small number of same-sex couples was excluded from the analysis. When one or more answers from one or both of the partners were missing, the couple is not included in the analysis.

Proxy interviews are allowed when a sample individual is not available for interviewing. As this can have an impact on the accuracy of the reply provided, we will investigate in Section 14.5 the impact of proxy interviews on the gap in deprivation between partners.

The analysis include all EU Member States except Denmark, the Netherlands, Finland and Sweden, where individual data on deprivation were only collected for the selected respondent and not for all adults in the household (see Chapter 2).

14.3. Descriptive analysis

In this section, we first present, for the pooled set of countries, the distribution of the nine possible combinations of answers (given the three possible answers above) among couples for each item. We then look at differences in deprivation for each item within couples by country. The descriptive analysis then proceeds by aggregating the six items into a deprivation scale for each individual, and computing the 'deprivation gap', that is, the difference between the scale values for wives and husbands.

14.3.1. Intra-couple differences in access to individual items

Figure 14.1 shows the proportion of couples providing the same or diverging responses, for the pooled set of countries.

To a certain extent, the proportion of people having the item affects the degree of concurrence or divergence: items possessed by nearly the whole population have a high probability of being possessed by both partners (the residual category in Figure 14.1).

Figure 14.1 shows only the categories of couples in which at least one partner lacks the item. It shows that in a majority of such couples both partners lack the item for the same reason (i.e. concurring couples, two green categories in Figure 14.1). However, a non-negligible proportion of couples diverge (more than one third of couples in which at least one partner lacks the item, except for internet access). The degree of concurrence on the internet item is probably due to the way the question was asked. Adults were asked if they had access to the internet for personal use at home. A large degree of similarity is therefore expected for those living under the same roof.

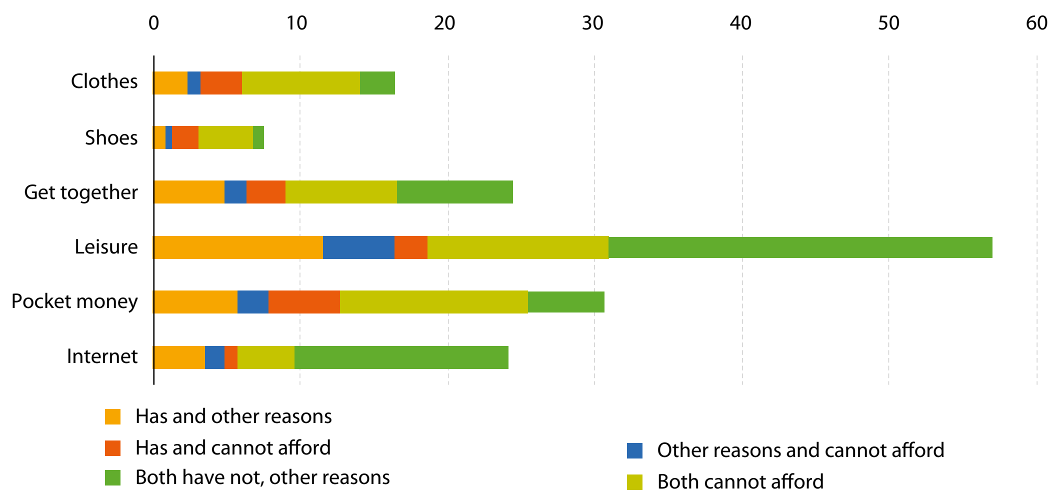
In view of the degree of divergence highlighted in Figure 14.1, it is interesting to investigate if divergence is gender-specific.

14.3.2. Gender differences in (enforced) deprivation of individual items

To investigate whether or not women and men have equal chances of being the disadvantaged partner in diverging couples, we grouped the three answer options (have; cannot afford; do not have for any other reason) into the binary concept of deprivation. Two concepts of deprivation can be defined.

- In the simple lack concept, all people lacking the item are considered deprived, whatever the reason why they do not have the item (affordability or other).

Figure 14.1: Percentage of couples providing the same or diverging responses, EU pooled data, 2015
(%)



Reading note: In 38 % of couples, both partners lack leisure for the same reasons (either affordability or other reasons). In 19 % of couples, the answer of both partners diverges. In 12 % of couples, one partner has leisure activities, but the other partner lacks them for other reasons than affordability.

Source: Authors' computations, UDB September 2016.

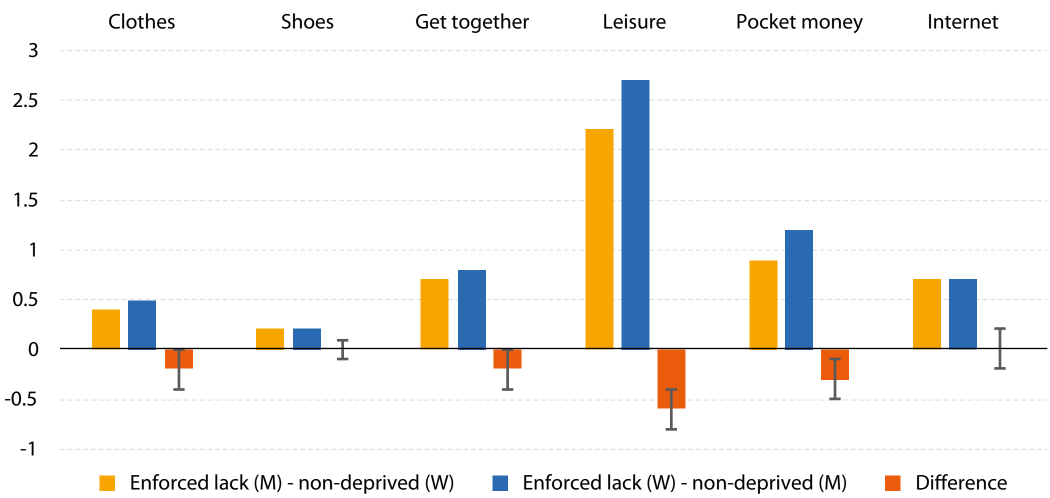
- In the enforced lack concept, only people who lack the item because of affordability (and not for any other reason) are considered deprived.

The second definition is the one used in the large majority of publications related to deprivation, and in the definition of the EU MSD indicator. As differences might be the result of different tastes (e.g. having no interest in a hobby), rather than differential access to the household's resources, enforced lack is also the definition we use in the rest of this chapter. However, we replicated our analysis using the simple lack concept instead, in order to test whether or not differences within couples are due to different subjective assessments of the reason why the item is lacking (cannot afford versus other reasons). It is conceivable that some partners do not want to admit that they lack an item – when the other partner has it – because they cannot afford it, in order to maintain the illusion of fair distribution. In those cases, differences might show up when the simple lack concept is applied, which would remain hidden with the enforced lack concept. These results are available on demand and do not substantially change the main conclusions of this paper.

Figure 14.2 presents the proportion of diverging couples when the enforced deprivation status of each partner is taken into account. It shows that gender differences in deprivation, although generally small, are significant and to the disadvantage of women, except for internet access, in which there is no significant difference. For the other items, they range from 0.2 p.p. (shoes) to 1.9 p.p. (pocket money).

Table 14.1 presents the significant differences (among diverging couples) between the proportion of couples in which the woman is disadvantaged (based on the enforced lack concept) and the proportion in which this is the case for the man, by country and by item. In other words, a negative value indicates that the proportion of couples in which the woman is the only partner deprived is significantly higher than the proportion in which the man is in this situation. The table shows that,

Figure 14.2: Distribution of couples according to the deprivation status of the two partners, by item, EU pooled data, 2015
(%)



Note: 95 % confidence intervals of the differences in the proportion of couples are presented. M: Man; W: woman.

Reading note: The proportion of couples in which the woman is the only partner deprived of leisure, whereas her partner can afford it, reaches 4 %. The proportion of couples in which the man is in this situation reaches 3.1 %. The difference reaches 0.9 p.p. and is significantly different from zero.

Source: Authors' computations, UDB September 2016.

in countries and for items where the difference is significant, the proportion of couples in which the woman is the only partner deprived is higher than the proportion in which the man is in this situation, showing a systematic gender-specific pattern (the only exception is for leisure in Cyprus). It also shows that the difference (between the two proportions) is far larger in many countries than it is at the overall EU level.

Shoes and the internet are the two items for which the difference is least often significant across the EU countries. A second group is composed of items such as clothes and getting together with friends, for which the difference is significant in around 10 countries. The items that lead to higher gender differences are those related to pocket money (for which the difference is significant in almost all countries) and leisure activities (significant in 16 countries).

The countries in which gender differences within couples concern a larger set of items are Romania (all items), Bulgaria, France, Latvia, Austria, Portugal and Slovakia. It is notable that the countries in which these gender differences are larger or occur

Table 14.1: Difference between the percentage of couples in which the woman is deprived of the item and the man is not, and the percentage of couples in which the man is the only partner deprived of the item if significantly different from 0 (*p* = 0.05), enforced lack, by country, 2015 (p.p.)

Member State	Clothes	Shoes	Leisure	Pocket money	Get together	Internet
Romania	–2.2	–2.2	–1.4	–2.3	–1.5	–1.5
Portugal	–1.0		–1.5	–7.0	–1.4	
France	–0.7		–1.4	–3.7	–0.4	
Slovakia	–1.7		–1.6	–2.3	–1.2	
Austria	–1.0		–2.3	–2.0		–0.5
Bulgaria	–2.3	–2.6		–2.0	–2.6	
Latvia	–2.8	–1.4	–1.3	–1.4		
Greece			–3.8	–3.7	–1.4	
Croatia			–1.1	–3.4	–1.2	
Hungary	–2.3		–2.3	–2.0		
Slovenia	–0.3		–0.9	–0.3		
Lithuania	–1.6		–3.4		–1.9	
Cyprus			2.1	–2.1		
Spain			–0.8	–1.6		
Estonia			–1.1	–1.2		
Poland			–2.1	–0.8		
Italy				–1.8		
Czechia				–1.4		
Luxembourg				–1.1		
Belgium				–1.0		
Ireland						
Malta						

Note: Countries ordered by number of items for which there are significant differences and, when that is equal, by difference for pocket money.

Reading note: In Romania, the difference between the percentage of couples in which the woman is deprived of the item and the man is not and the percentage of couples in which the man is the only partner deprived of the item is significantly different from 0 (*p* = 0.05) for all six items.

Source: Authors' computations, UDB September 2016.

for more items than the EU average include some of those with the highest overall levels of deprivation (Bulgaria, Latvia, Romania), but also some countries in which deprivation is lower than the EU average (France, Austria). On the other hand, at the bottom of the table we find only countries with relatively low proportions of people living in deprivation.

These first descriptive results confirm previous conclusions in the literature: in a majority of couples there is no difference in individual replies to the deprivation questions. However, a substantial proportion of couples diverge (at least one third of couples in which one or both partners lack the item, except for internet access). Among diverging couples, at EU level and for all items except internet access, the percentage of couples in which the woman is the only partner who is deprived is close to, yet always slightly higher than, the proportion of couples in which the man is in this situation. Differences vary by item and country, but when statistically significant they are always to the disadvantage of women.

The next section will look at the degree of concentration of this disadvantage once the six items are aggregated into a deprivation scale.

14.3.3. Gender differences in the number of items lacked

We now focus on the cumulation of deprivations. The six items are aggregated into an unweighted deprivation scale for each individual (ranging from 0 to 6). We did not weight the items (for instance by the proportion of individuals having the item within each country), as the results are more easily interpretable without weighting ([163]). For each couple, the difference between the sum of deprivations of the woman and the man is computed; this is 'the gender deprivation gap'.

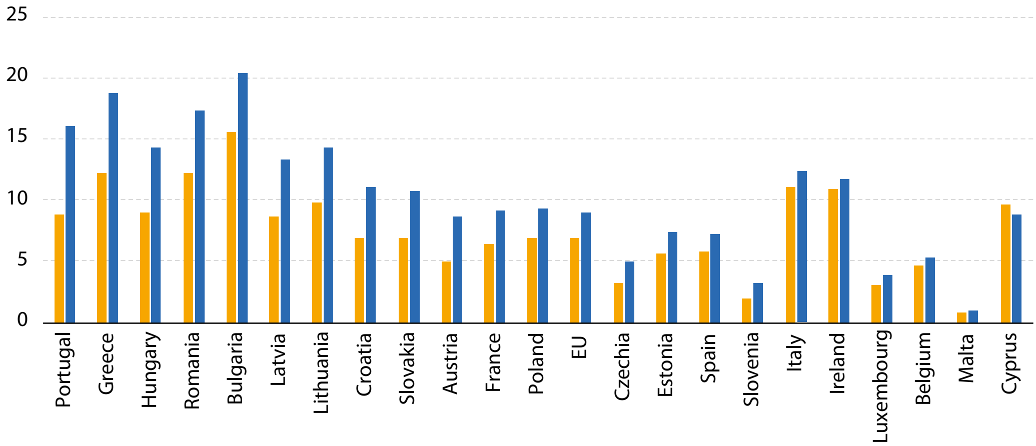
The deprivation scale cumulates the divergences at item level, described in the previous section. Differences in deprivation within couples are not uncommon (in total, partners have different deprivation scores in almost 16 % of all couples), and deprivation gaps to the disadvantage of the man (6.5 %) are nearly as frequent as deprivation gaps to the disadvantage of the woman (9.2 %); see Figure 14.3 (EU average bar). Yet, on aggregate, the difference is clearly in disfavour of women. Figure 14.3 also presents these figures at national level, and confirms that in most countries the proportion of couples in which the woman is the disadvantaged partner exceeds the proportion in which the man is in this situation. Figure 14.4 presents the 95 % confidence interval of the difference in these two proportions and shows that there are only a few countries where the proportion of couples in which the disadvantaged partner is the woman does not significantly exceed the proportion in which it is the man (Belgium, Ireland, Cyprus, Luxembourg and Malta). Countries where the difference is the highest include Portugal, Greece, Hungary, Romania and Bulgaria.

The deprivation gap between the two partners amounts in most cases to one or two items out of six, rarely more (less than 1 % of the sample). In the remainder of the chapter, we therefore focus on the existence of a deprivation gap, ignoring the number of items that constitutes this difference.

It is worth also keeping in mind that the deprivation items used in this chapter measure only low standards of living, and do not differentiate among those whose standards of living exceed a certain threshold. Therefore, differences in the standard of living between men and women when they are both above that threshold are not measured.

([163]) A discussion of the impact of weighting on the EU material deprivation indicator can be found in Guio (2009).

Figure 14.3: **Percentage of couples where the woman/man suffers from more deprivations than her/his partner, by country, 2015**
(%)

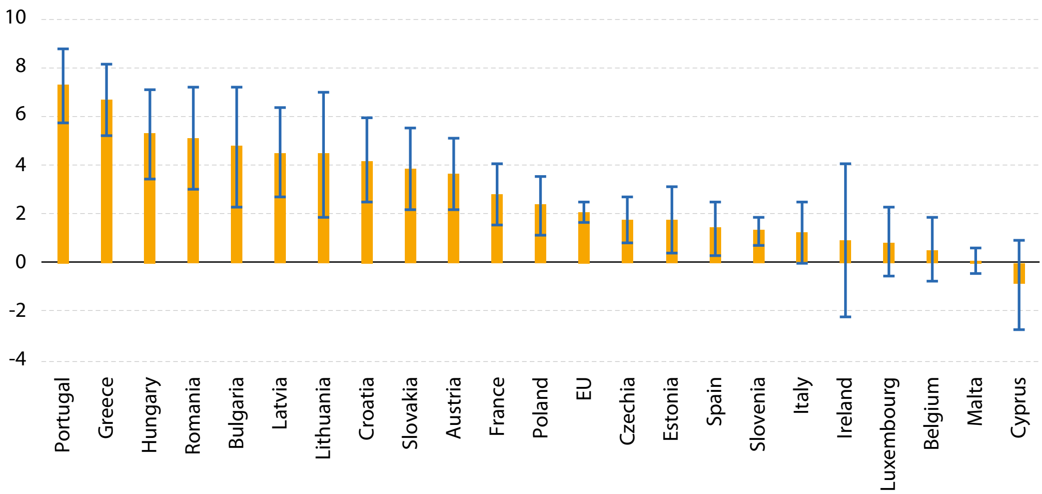


Note: Countries are ranked according to the difference between the percentage of couples in which the woman suffers from more deprivations than her partner and the percentage of couples in which the man suffers from more deprivations than his partner.

Reading note: In Portugal, the percentage of couples in which the woman suffers from more deprivations than her partner reaches 16 % and the percentage of couples in which the man suffers from more deprivations than his partner reaches 9 %.

Source: Authors' computations, UDB September 2016.

Figure 14.4: **Difference in the percentage of couples in which the woman suffers from more deprivations than her partner and the percentage of couples in which the man suffers from more deprivations than his partner, by country, 2015**
(p.p.)



Note: 95 % confidence intervals of the differences in the proportion of couples are provided.

Reading note: Positive differences indicate that women are more often disadvantaged in couples than men.

Source: Authors' computations, UDB September 2016.

14.4. Determinants of the gender deprivation gap

As discussed in previous sections, the deprivation gap depends to a certain extent on the deprivation level of couples. When couples are not deprived of any item, it is obviously impossible to observe a deprivation gap. Similarly, when couples are deprived of all items, there is no deprivation gap either.

To take into account the endogeneity of the deprivation level, we have set up a system of three equations estimating:

1. the probability of suffering from deprivation at couple level;
2. the probability that the deprivation gap in the couple is to the disadvantage of the woman; and
3. the probability that the deprivation gap in the couple is to the disadvantage of the man.

Independent variables in the first equation (which estimates the deprivation risk of the couple) include the usual sociodemographic variables used in deprivation analyses (see Chapters 8 and 13 of this volume):

- household equivalised income (expressed in PPS),
- higher age of the partners,
- educational attainment of the more highly educated partner,
- housing cost overburden,
- debt overburden,
- difficulties in making ends meet,
- work attachment of partners,
- health problems (at least one partner having limitation in daily activities),
- number of dependent children.

Independent variables in the substantive regressions (deprivation gap at the disadvantage of the woman/the man) include the following aspects.

- The age of partners or their age difference may impact on sharing of resources. Similarly, the presence of children may also have an impact in case of limited resources. Cantillon et al. (2015) found that the presence and number of children had a stronger effect on individual deprivation for women than for men. This may be interpreted as an indication that mothers may try to shield their children from deprivation by spending less on their own needs.
- Two variables capture the financial power of partners: the work attachment of partners and the share of the woman's personal income in the total personal income of both partners.
- Given the partly subjective nature of the deprivation questions, the mode of interviewing may be important to explain gender differences in deprivation (face-to-face interviewing, with answers recorded either on paper or on a computer; telephone interviewing; CAWI; or self-administered questionnaire). Answers may also be affected by the presence of the partner when respondents are interviewed (see Cantillon and Newman, 2005), but we have no information on this.
- Proxy interviews are allowed when a sample individual is not available for interviewing; the proxy respondent is generally the partner. A proxy respondent might be hesitant to say that the reason her or his partner lacks an item is that the partner cannot afford it, especially when the respondent previously gave a different answer to the same question when it referred to her- or himself. A case could be made for excluding proxy interviews from the analysis sample. We have not done so, as that would result in a large reduction in the number of observations for some countries. Moreover, the resulting sample would be selective, as most proxy interviews are for persons who are at work. We therefore opted to test the impact of proxy interviews on deprivation gaps.
- Note that our sample includes complex households, in which the couple lives together with other adults. We controlled for this in the regression. A sensitivity analysis excluding these households did not alter our conclusions.

Tables 14.2 shows the results. In the first part of the table, the results of the first equation confirm previous analyses of deprivation (see also Chapters 8 and 13 of this volume). The probability that at least one partner lacks one or more items decreases with the income level, the presence of self-employed persons (owing to the difficulty of adequately measuring self-employment income in surveys) and the educational attainment (which captures permanent income). It correlates with the level of costs (housing costs, number of children) and with the burden of debt. Couples in which only one partner works (woman or man), or in which neither partner works, suffer from a higher risk of deprivation than those in which both partners work, even when household income is taken into account. Large country fixed effects are significant, although cross-country differences in household income in purchasing power standards are included in the model. This confirms the findings of Chapter 13 that macro-level determinants, such as the level and efficiency of welfare system and the provision of in-kind services, have an impact on the degree of deprivation of the whole population.

In the second part of Table 14.2, the results of the substantive regressions are of interest regarding our research question about the main determinants of the gender-specific deprivation gap within couples. The second equation models the probability that the woman suffers from a higher number of deprivations than the man (compared with the probability of no gap or a gap to the disadvantage of the man). The third equation explains the probability that the man suffers from a higher number of deprivations than the woman (compared with the probability of no gap or a gap to the disadvantage of the woman).

We find that the joint deprivation status of the couple increases the deprivation gap (both when it disadvantages the woman and when it does the man). When the couple is deprived, the probability of finding a deprivation gap increases.

The work attachment of wives and husbands has a symmetrical impact on the gender differences in deprivation in the sense that, when one partner works and the other does not, this increases the risk of a deprivation gap to his or her partner's disadvantage. Couples in which neither partner works and those in which both work do not differ from each other in terms of the deprivation gap, once the joint deprivation level is controlled for. Similarly, the higher the share of the couple's income that the woman earns, the higher the probability that the deprivation gap disadvantages her man rather than herself.

As regards demographic variables, the results show that the presence of children is associated with a smaller risk of a deprivation gap for both women (only for large families) and men (all families with children); see Daly and Kelly (2015), for similar findings. This finding contrasts with those of Cantillon et al. (2015), who found that the presence and number of children had a stronger effect on individual deprivation for women than it had for men.

The partners' ages have a positive but marginal effect on the gender deprivation gap in any direction. The age difference does not have a significant impact.

Our results also show that the use of proxy interviews has an impact on the gender deprivation gap: when the woman (man) is not available to reply to the questionnaire and is replaced by another household member, this decreases the probability of a deprivation gap to her (his) disadvantage. The odds ratios are identical for men and women. This is an important result, which has implications for data collection.

The mode of interviewing has an impact, with self-administered and CAWI questionnaires leading to a larger gap (to the disadvantage of women). The privacy of these two modes of interviewing may indeed help to declare self-deprivation, particularly when this differs from that of the partner.

Some country fixed effects remain significant when other explanatory variables are taken into account (including mode of interviewing). Belgium was chosen as the reference, having low/medium proportions of couples in which there is a deprivation gap, with no difference between men and women. As highlighted above, Malta and Slovenia appear to be outliers, with significantly smaller gaps than all other countries. Investigation in the data collection method applied are needed in these countries. The other countries can be grouped as follows.

- Relatively high effects to the disadvantage of women are registered for Bulgaria France, Austria and Portugal, although for men there is no significant difference from the reference country once the other variables in the model are controlled for.
- A second group of countries (Czechia, Greece, Lithuania, Hungary, Romania, Slovakia) have a smaller risk of a deprivation gap to the disadvantage of men than expected on the basis of the variables taken into account in the model, although the proportion of couples with a disadvantage for women does not differ from the reference country. Spain has a negative fixed effect for both sexes.
- The other countries (Estonia, Ireland, Croatia, Italy, Cyprus, Latvia, Luxembourg and Poland) do not differ significantly from the reference country when we control for the variables included in the model.

Could the differences between countries that are not explained by individual characteristics, as revealed by the country effects in Tables 14.2 and 14.3, be due to the variation across countries in the extent of income pooling within couples? To approach this question, we used the results of the analysis by Ponthieux (2017), using the special module of EU-SILC 2010. She combines the answers of both partners to the questions about income pooling into a single variable, measuring the pooling regime of the couple (full pooling, partial pooling or no pooling). We found no correlation between the countries' fixed effect on the woman's deprivation gap and the proportion of all couples having a full pooling regime. Although this evidence is only suggestive, it shows that there is no straightforward relationship between the degree of income pooling and deprivation differences within couples. As Bennett (2013) emphasises, it would be a mistake to try to read off inequality in outcomes from the type of allocation systems within the household. This is confirmed by Cantillon, Maître and Watson (2015), who use data on individual deprivation collected in the Irish survey combined with data on intra-household sharing of resources from the 2010 ad hoc module of EU-SILC (as individual items were only collected in Ireland, they are limited to the Irish data). They found that the couple's financial regime did matter for individual deprivation, but not always in the way that might have been expected. Where couples pooled all their personal incomes, and controlling for the level of income and other factors, the level of individual deprivation tended to be higher. Rather than income pooling, it seems that the degree of shared decision-making influences intra-household differences in deprivation. They found that couples who share decisions had a lower risk of individual deprivation for both partners, controlling for household income and the degree of income pooling ([164]).

([164]) Bárcena-Martin et al. (2016), using the same EU-SILC 2010 special module, study the relation between the financial regime of a couple and deprivation, but at household level. Their results suggest that sharing decisions, when controlling for the effects of other socioeconomic determinants, is associated with lower levels of household deprivation.

Table 14.2: Estimates of a system of three logistic regressions equations: deprivation of the couples, deprivation gap at the disadvantage of the woman, deprivation gap at the disadvantage of the man, marginal effects, 2015

Probability that at least one partner lacks one item		
Parameter	Estimate	Significance
Intercept	4.04	< 0.0001
Log household income (PPS)	−0.53	< 0.0001
Both partners at work (ref.)		
No partner at work	0.12	< 0.0001
Woman is the only partner at work	0.28	< 0.0001
Man is the only partner at work	0.18	< 0.0001
Higher age of the two partners	−0.01	< 0.0001
Health problems	0.2	< 0.0001
Difficulties in making ends meet	0.86	< 0.0001
Heavy housing cost overburden	0.24	< 0.0001
Heavy debt overburden	0.2	< 0.0001
Self-employment	−0.16	< 0.0001
High education (ref.)		
Low education	0.22	< 0.0001
Medium education	0.22	< 0.0001
Number of children	−0.01	0.008
Belgium (ref.)		
Bulgaria	0.72	< 0.0001
Czechia	−0.5	< 0.0001
Estonia	0.16	0.06
Ireland	0.37	< 0.0001
Greece	0.49	< 0.0001
Spain	−0.19	< 0.0001
France	0.23	< 0.0001
Croatia	−0.69	< 0.0001
Italy	−0.07	0.02
Cyprus	−0.25	0.01
Latvia	0.42	< 0.0001
Lithuania	0.92	< 0.0001
Luxembourg	−0.58	0
Hungary	0.5	< 0.0001
Malta	0.2	0.17
Austria	0.51	< 0.0001
Poland	−0.12	0
Portugal	−0.05	0.2
Romania	0.95	< 0.0001
Slovenia	−0.1	0.2
Slovakia	0.01	0.84

Table 14.2: continued

Parameter	Probability of a deprivation gap to the disadvantage of:			
	The woman		The man	
	Est.	Sign.	Est.	Sign.
Intercept	−2.58	< 0.0001	−2.65	< 0.0001
Share of woman's income in the income of the couple	−0.51	< 0.0001	0.65	< 0.0001
Proxy interview for the woman	−0.17	< 0.0001	0.08	< 0.0001
Proxy interview for the man	0.01	0.56	−0.18	< 0.0001
Higher age of the two partners	0	0	0	0
Age difference between partners	0	0.84	0	0.95
Both partners at work (ref.)				
Woman is the only partner at work	0.04	0.1	0.23	< 0.0001
Man is the only partner at work	0.23	< 0.0001	0.07	0.02
No partner at work	0.03	0.2	0.02	0.43
2 adults, no child (ref.)				
2 adults, 1 child	−0.03	0.25	−0.12	< 0.0001
2 adults, 2 children	−0.02	0.52	−0.19	< 0.0001
2 adults 3 children or more	−0.08	0.01	−0.3	< 0.0001
More than 2 adults with children	−0.02	0.46	−0.12	< 0.0001
CAWI or self-administered (ref.)				
PAPI	−0.08	0.05	−0.06	0.17
CAPI	−0.08	0.01	−0.01	0.77
CATI	−0.06	0.09	−0.02	0.57
At least one partner deprived	2.24	< 0.0001	1.9	< 0.0001
Belgium (ref.)				
Bulgaria	0.23	0	−0.1	0.1
Czechia	0.04	0.63	−0.33	0
Estonia	0.21	0.14	0.18	0.19
Ireland	−0.08	0.5	0.2	0.05
Greece	0	0.98	−0.13	0.05
Spain	−0.26	< 0.0001	−0.15	0
France	0.19	0	0.03	0.49
Croatia	0.05	0.61	−0.18	0.06
Italy	0.01	0.83	−0.03	0.5
Cyprus	−0.26	0.12	−0.16	0.32
Latvia	0.06	0.54	−0.2	0.06
Lithuania	−0.06	0.52	−0.27	0
Luxembourg	−0.01	0.97	0.03	0.92
Hungary	0.05	0.38	−0.25	< 0.0001
Malta	−0.83	0.01	−0.56	0.08
Austria	0.28	< 0.0001	0.04	0.54
Poland	0.08	0.18	−0.07	0.23
Portugal	0.37	< 0.0001	−0.18	0
Romania	−0.06	0.37	−0.23	0
Slovenia	−0.75	< 0.0001	−0.95	< 0.0001
Slovakia	0.04	0.67	−0.19	0.04

Note: CAPI, computer-assisted personal interview; CATI, computer-assisted telephone interview; CAWI, computer-assisted web interview (or self-administered); est., estimate; PAPI, paper and pencil interview; sign., significance.

Source: Authors' computations, UDB September 2016. Number of observations: 118 525. Weighted estimation.

14.5. Conclusions

This chapter highlights the value of opening the black box of the intra-household distribution of goods and services by looking at individual differences in deprivation. In conventional analyses of poverty and deprivation based on the household level, partners in a couple are assumed to have an equal living standard.

We analysed six deprivation items collected at individual level. Our results show that, within couples, the deprivation level differs between partners in a non-negligible number of cases in a range of European countries. The proportion of couples in which the partners gave diverging answers is limited for items such as clothes (7 %) and shoes (3 %), but much higher for items such as leisure (19 %) and pocket money (13 %). In these couples, the partners do not provide the same reply to the three-option questions. Once we combine answer categories to define the enforced lack concept (so merging lack for other reasons with having the item), the number of couples in which there is a one-sided enforced lack (i.e. one partner does not have the item because she or he cannot afford it, and the other has it, or does not have it for other reasons) is much more limited, ranging from 2 % for shoes to 7 % for leisure and pocket money.

Divergence depends on the proportion of people lacking the item, as there can be no divergence when people have the item: this explains to a certain extent differences between items and countries.

Furthermore, divergence can be to the disadvantage of the man or of the woman. For all items except access to the internet, the gender difference, although generally small, is significant and to the disadvantage of women. At EU level, the difference ranges from 0.2 % for shoes to 1.9 % for pocket money, but it is larger in some countries.

When aggregating lack on the level of items into a deprivation scale for adults, and considering the difference between the scores on this scale of partners within couples, we find that there is no difference in 84 % of all couples (in fact, 59 % of all couples do not suffer from any enforced lack of the six items, so a deprivation gap cannot appear). Where it is different from zero, the intra-couple gender deprivation gap can go in either direction, but the situation in which the number of enforced lacks is higher for the woman (9.2 % of all couples) occurs more often than that in which the man is the one who is relatively disadvantaged (6.5 %).

Our analysis therefore confirms previous studies. In a large majority of couples, no imbalance in deprivation is apparent, mainly because both partners do not lack any item. Focusing on those couples in which at least one item is lacked by one partner, the proportion of diverging couples is substantial. Furthermore, even though the percentage in which the woman is the disadvantaged partner is close to that in which the man is in this situation, there is clear evidence that the intra-couple gender deprivation gap is systematically biased to the disadvantage of women.

One should be careful in drawing inferences from these findings on the intra-couple gender deprivation gap about the intra-couple distribution of economic resources. For individual couples, a gender deprivation gap can occur for a number of reasons, even if the partners have equal or equivalent access to resources. However, the finding that the distribution of the gender deprivation gap is systematically skewed to the detriment of women is an indication that deviations from an equal distribution of resources within couples disadvantage women more often than men. Conversely, the absence of a gender deprivation gap does not indicate that the intra-couple distribution of resources is equal or equitable. In a couple with a sufficiently high although unequally shared income, the partner who gets the lesser share may still have sufficient resources to escape deprivation. In other words, not finding an intra-couple deprivation gap does not constitute evidence that there is no inequality in the distribution of resources within couples. It would therefore be wrong to conclude that there is more intra-couple inequality in a wider sense in the countries where we find a large proportion of couples in which the gender-deprivation gap is to the detriment of the woman or the man. Unfortunately there are at present no good cross-country data on intra-couple inequality to corroborate this (see also Ponthieux, 2017).

As did earlier studies, we find that the work status of the partners and their share of joint income are important determinants of the intra-couple gender deprivation gap. A larger share of income for the female partner is associated with a smaller probability of a deprivation gap to her disadvantage, and a higher chance that her partner has a higher deprivation score than she has. The work attachment of wives and husbands has a symmetrical impact on the gender differences in enforced deprivation in the sense that when a partner is in paid employment, while the other is not, this reduces the risk of a gender deprivation gap to his or her disadvantage, while increasing it for the other partner.

The results of the multivariate analysis also suggest that national differences were not fully explained by the model and may be due to idiosyncratic factors. No relationship was found between these national differences and the popularity of the full pooling regime among couples.

As the quality of the data is crucial to present a correct picture of the gender deprivation gap within couples at EU level, there are a number of issues that need to be addressed in terms of data collection, before definitive conclusions can be drawn.

First, in some countries the data are not available at individual level for all the adults who compose the household, either because the information was collected only at household level or because only one respondent per household (the selected respondent) was interviewed. Moreover, among the countries for which individual information is available, some deviate strongly from the general pattern. Compared with the other countries, the number of diverging couples is extremely low in Malta and Slovenia. This deserves further investigation.

Second, our results show that the use of proxy interviews may have an impact on the deprivation status of the (absent) person in some countries. When the woman (man) is not available to reply to the questionnaire and is replaced by another household member, this decreases the probability that disadvantage vis-à-vis her (his) partner is observed. It is therefore very welcome that from 2021 the revised EU-SILC will limit the use of proxies for deprivation data, as is already done for other sensitive EU-SILC questions about adults related to well-being or health. Ideally, each member aged more than 15 years should be surveyed alone (see Cantillon and Nolan, 1998; 2001).

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Understanding the dynamics of poverty and social exclusion

15 In-work poverty and deprivation dynamics in Europe

Anne-Catherine Guio, David Marguerit and Ioana Cristina Salagean (165)

15.1. Introduction

The most recent data show that in the EU-27 about 1 in 11 workers was AROP and about 1 in 12 workers was experiencing MSD (see Chapter 1 for the definitions of AROP and MSD).

These figures show that work shields most, but certainly not all, of those living in the EU from economic hardship. This holds true whether hardship is measured by income or in non-monetary terms. A substantial share of workers are in-work poor or deprived, and their numbers have grown recently in many EU countries (Peña-Casas et al., 2019). This situation calls for an examination of the mechanisms that prevent working individuals from lifting their families out of being AROP and/or MSD, despite advanced economic development and the social safety nets established by European countries.

The dynamics of poverty and MSD for those in work are more complex than for the general population. For the population at large, the dynamics of being AROP / MSD are driven by changes in their AROP/MSD status only. In the case of in-work poverty/deprivation, two dimensions are involved: the change in activity status on the labour market (worker or non-worker) and entry into or exit from being AROP / MSD (poor/deprived or non-poor/non-deprived).

Only a handful of recent studies have analysed the dynamics of in-work poverty and material deprivation. However, analysis of whether someone exits or enters in-work poverty because of a change in their status on the labour market or because of a change in the risk of poverty/deprivation is crucial for public policies. This is because someone exiting (entering) in-work poverty because of changes in their labour market status does not imply the same response as someone exiting (entering) in-work poverty with no change in labour market status. As explained by Hick and Lanau (2018, p.662), who provide the most thorough descriptive analysis of dynamic in-work poverty and deprivation, focusing on the United Kingdom between 2010 and 2014:

'Examining in-work poverty transitions, and their inherent complexity, matters for at least two reasons. First, it provides us with a better understanding of the nature of in-work poverty itself. These are multiple trajectories that people can and do take from in-work poverty, and this requires us to acknowledge at the outset that not all working poverty exits are equal. On the contrary, policy will need to maximise the 'good' trajectories (exiting poverty) while minimising the 'bad' ones (exiting work). To do this, we first need to understand the nature and extent of these different trajectories. Second, as in-work poverty is a growing problem, understanding the ways that people do, in fact, move in and out of in-work poverty can help to identify policy solutions that can successfully reduce poverty amongst working households.'

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This chapter aims to study the extent of workers' mobility into and out of being in work AROP and MSD in EU-SILC countries, and assesses cross-national variation in mobility patterns, looking at 2-year transitions between 2016 and 2017. It also analyses which characteristics and triggers, that is, events that are contemporaneous with entry or exit, are associated with such transitions and if these triggers explain variations in transitions among EU-SILC countries.

This chapter is organised as follows: it first discusses the definitions and measurement issues (Section 15.2), and then presents the data in Section 15.3. Section 15.4 highlights the dynamics of in-work poverty and deprivation. The econometric strategy and the results are shown in Section 15.5. Section 15.6 concludes.

15.2. Definitions and measurement

The extent and dynamics of in-work poverty and in-work deprivation clearly depend on the definitions given to the notions of 'work', 'poverty' and 'deprivation', on which the existing literature does not agree (see Crettaz, 2011, for a review of issues in the measurement of in-work poverty). We rely on definitions established for the EU's official commonly agreed in-work poverty indicator (Bardone and Guio, 2005) and use the same approach to define the in-work MSD indicator.

'Work' is understood to mean any form of work for pay or profit, where pay also includes payments in kind. A 'worker' is any person aged at least 16 whose self-declared economic activity status was either 'employed' or 'self-employed' for at least half the number of months for which the information on the self-declared economic activity status is provided during the income reference year (i.e. 6 months in the case of a full record for the full year). EU-SILC survey respondents are instructed to determine their monthly main economic status based on how they spent the majority of their time. Persons who are in the process of setting up, working for or in charge of operating their own business, professional practice or farm are also considered workers, namely self-employed workers. People on maternity or paternity leave are included among workers; those on full-time parental leave are excluded.

Setting a number of months to define the self-declared economic activity status may affect the dynamics of in-work poverty if a lot of people move around this threshold from one year to the other. People working 5 (7) months in 2016 can move into (out of) in-work poverty because they work 1 more (less) month in 2017, but with little impact on annual earnings and work involvement. Our checks show that these situations count for fewer than 1 % of all the transitions to/from in-work poverty and that such transition have no impact on our results. A worker is considered 'working poor' if he or she is AROP.

The 'in-work poverty rate' expresses, the percentage of AROP individuals in the total working population. The fact that work is an individual characteristic whereas AROP is a household attribute creates a conceptual difficulty for the measurement of in-work poverty. Unlike others (e.g. Hick and Lanau, 2018), who count poor all members of the household as working, our relative headcount measurement of in-work poverty only includes individuals who are themselves working.

This chapter uses the EU's new MSD indicator, proposed by Guio et al. (2017) and adopted by the EU in March 2017. As explained in Chapter 1, the 13-item scale includes both household-level items and items collected at individual level for adults (aged more than 15). This means that adults living in the same household may show different deprivation levels.

As a more absolute poverty measure capturing differences of living standards within the EU, the rate of material and social deprivation is a useful addition to the relative poverty measures (see Guio, 2005; Nolan and Whelan, 2010; Fusco et al., 2011; Guio et al., 2012).

15.3. Data

We use the cross-sectional data set to provide descriptive information on the level of in-work poverty and deprivation in the EU-SILC countries. We then use the longitudinal component of EU-SILC for 2016–2017 (income years 2015–2016) to study year-to-year trajectories to and from in-work poverty/deprivation. This data set includes all EU Member States in 2020 except Germany, Ireland and Slovakia. It also includes two non-EU EU-SILC countries: Norway and Serbia. The 2016–2017 transition is the last available to date that includes the data about the new MSD indicator.

The data are missing for at least 1 year for the MSD indicator in Belgium and Serbia. These two countries are therefore excluded from our analysis of in-work deprivation. Similarly, income data from Bulgaria could not be used for computing the transition of in-work poverty because of problems with the reliability of the income variable.

At national level, when the sample size is lower than 50 observations for the transition studied, the figures are not presented for the country.

Some serious constraints on longitudinal analyses are imposed by the design of EU-SILC as a rotational panel with a duration of (at least) 4 years (see Chapter 17 of this volume). In the 4-year rotational scheme, individuals and households are interviewed for 4 consecutive years, and each year about a quarter of the sample is renewed. That is the main reason why we focus in this chapter on the dynamics over a 2-year period, as this allows us to work with three quarters of the original sample. Looking at transitions during the 4 years of the panel would have meant working with at most one quarter of the full sample, which would have resulted in an insufficient sample for some groups of workers in many countries. However, even when using only a 2-year window, one should keep in mind that the reduction in sample size may cast some doubts on whether or not the population sample is representative when analysing rather low-frequency phenomena such as in-work poverty and deprivation transitions. Moreover, in small EU-SILC countries, especially where the incidence of in-work poverty and deprivation is low, small sample sizes may limit or even preclude dynamic analysis.

We refer subsequently to the subset of individuals aged 16 or more who were present both in 2016 and in 2017 as the 'pooled data set'. To make it easier to interpret the nature of transitions, people who leave the labour market in 2017 because of retirement, permanent disabilities or compulsory military or community service are excluded from this data set.

15.4. Descriptive analysis

15.4.1. Cross-sectional results

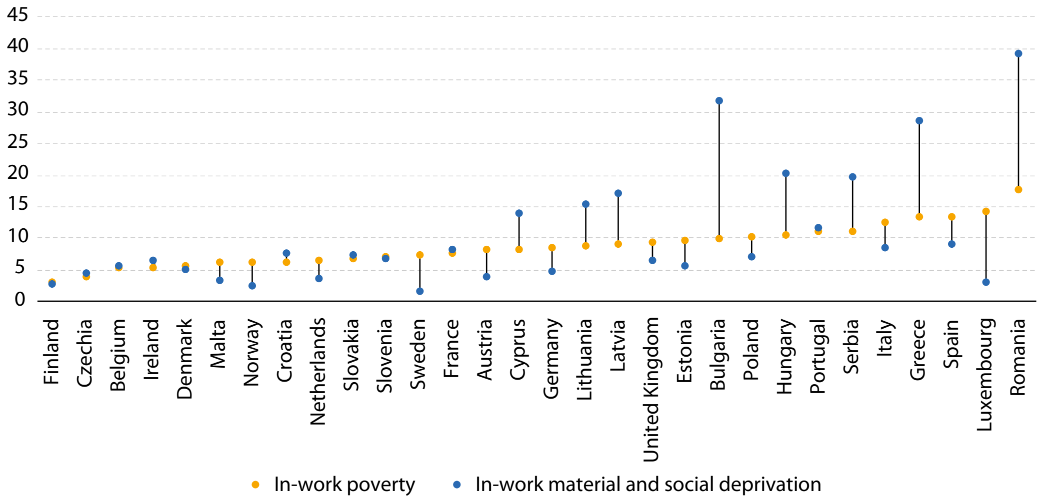
Income poverty and deprivation indicators need to be considered together to understand country differences. This is why both indicators were agreed at EU level, for the whole population, and are commonly used at national and EU levels to monitor progress.

However, to measure in-work hardship, the portfolio of commonly agreed EU indicators only relies on a purely monetary approach. To date, in-work MSD has not been included in the portfolio of EU commonly agreed indicators. Figure 15.1 shows, however, the benefit of using both concepts to measure in-work hardship, as the association between the monetary and the non-monetary measure of poverty is known to be rather weak (see among others Fusco et al., 2011; Whelan et al., 2003).

In the least affluent (Bulgaria, Greece, Hungary, Romania) and the most affluent countries (Luxembourg, Sweden), the two measures yield very different headcount rates, as is the case for the total population. In the former group, the prevalence of in-work MSD is twice as high as that of in-work poverty (three times in Bulgaria). The most affluent countries are in the opposite situation: in-work poverty affects five times more workers than in-work MSD.

These figures offer a static view of in-work hardship and do not inform us about any changes and mobility of the people involved. The next section explores the transitions to and from in-work poverty/deprivation.

Figure 15.1: In-work poverty and in-work MSD rates, 2017
(% of total working population)



Note: Countries ordered by in-work poverty rate. The sample includes any person aged at least 16 whose self-declared economic activity status was either 'employed' or 'self-employed' for at least half of the income reference year.

Reading note: In Romania, 39 % of workers suffer from MSD although 17 % are AROP.

Source: Authors' computations, UDB March 2019, weighted by RB050.

15.4.2. Year-to-year trajectories to and from in-work poverty/deprivation, aggregate level

Dynamic analyses of in-work poverty may take various approaches. The first aims to measure 'persistence', that is, the duration of poverty experienced by workers either continuously or recurrently over a period. At EU level, one of the commonly agreed indicators measures the persistence of income poverty and identifies the proportion of people who are income poor at one point in time, and for at least 2 of the 3 preceding years. This requires use of the 4-year duration of the panel.

A second strategy is to assess 'mobility' from one year to the next, typically by describing the rate of entry into working poverty for previously non-poor individuals and the poverty escape rate for previously poor workers. This is the approach chosen in this chapter, as it is less demanding in terms of length of the panel. 'Recurrence' of in-work poverty, meaning a return to poverty after an earlier exit, is also a form of mobility, but requires a longer observation window and will not be included in the analysis.

Year-to-year transitions in in-work poverty/deprivation are driven by changes in both activity status and poverty/deprivation status. Each year, there are four possible situations:

- worker and poor/deprived,
- non-worker and poor/deprived,
- worker and non-poor/deprived,
- non-worker and non-poor/deprived.

Looking at transitions over a 2-year period, 16 types of trajectories are possible: in the first year, a person is in one of the four situations listed above and in the second year must again fall into one of the four categories.

Table 15.1 draws on the 2-year pooled data set (see Section 15.3) to show the percentage of people aged 16 or more who transitioned to each of the four in-work poverty statuses in year T + 1 as a share of individuals holding each status in year T. The sum of every row is 100 % of transitions from the status presented in the first column.

Table 15.1 shows that the working poor are more mobile than those in other statuses. Around 56 % of the initially working poor remain working poor in the second year. When workers exit in-work poverty, it may be thanks to an exit from income poverty while individuals keep working (37 %), which is arguably a favourable transition. However, a second route out of in-work poverty is for individuals to leave work while remaining poor (5 %). Such exits could be considered unfavourable transitions. A small proportion of in-work poor both escape poverty and stop working (2 %).

Among non-poor workers, 3 % become in-work poor, and 3 % stop working and remain non-poor. The rest of the non-poor worker population remains in that situation.

A worrying figure, already highlighted by Hick and Lanau (2018) for the United Kingdom, is that in Europe poor workers are far more likely than non-poor workers to become poor and workless in the second year (5.4 % versus 0.6 %).

Another important result is that, among non-working poor persons who find a job in the second year, half do not manage to escape poverty (8.8 ÷ (8.8 + 9.4)). Similar proportions of non-working poor find a job and escape poverty or find a job and remain in poverty (9 %); see Grzegorzewska and Thévenot (2014) for a similar result.

Table 15.1: In-work poverty trajectories between T and T + 1, as a share of individuals in each status in T, 2016–2017, pooled data set

(%)

Status in T (2016)	Status in T + 1 (2017)				Total
	Worker poor	Non-worker poor	Worker non-poor	Non-worker non-poor	
Worker poor	55.7	5.4	36.7	2.3	100.0
Non-worker poor	8.8	64.2	9.4	17.7	100.0
Worker non-poor	3.1	0.6	93.4	2.8	100.0
Non-worker non-poor	1.0	8.3	16.2	74.5	100.0

Note: Workers include any person aged at least 16 whose self-declared economic activity status was either 'employed' or 'self-employed' for at least half of the income reference year, and non-workers are those with self-declared economic activity of 'unemployed', 'student' or 'fulfilling domestic tasks and care responsibilities'.

Reading note: 36.7 % of the poor workers in T (2016) become non-poor workers in T + 1 (2017).

Source: Author's computations, UDB 2019-1, weighted by RB062.

Table 15.2: In-work deprivation trajectories between T and T + 1, as a share of individuals in each status in T, 2016–2017, pooled data set
(%)

Status in T (2016)	Status in T + 1 (2017)				Total
	Worker deprived	Non-worker deprived	Worker non-deprived	Non-worker non-deprived	
Worker deprived	54.7	4.9	37.4	2.9	100.0
Non-worker deprived	8.3	51.2	9.4	31.1	100.0
Worker non-deprived	3.0	0.3	93.6	3.0	100.0
Non-worker non-deprived	1.1	6.6	16.6	75.6	100.0

Note: Belgium and Serbia are excluded because of missing values for some deprivation variables for at least 1 year, and Denmark, Norway and Sweden because their sample sizes are lower than 50 for some of the categories. Workers include any person aged at least 16 whose self-declared economic activity status was either 'employed' or 'self-employed' for at least half of the income reference year, and non-workers have a self-declared economic activity of 'unemployed', 'student' or 'fulfilling domestic tasks and care responsibilities'.

Reading note: 38.4 % of the deprived workers in T (2016) become non-deprived workers in T + 1 (2017).

Source: Author's computations, UDB 2019-1, weighted by RB062.

Table 15.2 offers equivalent information on the deprivation status. This confirms our previous conclusions. Slightly more than half of the working deprived in the first year remain working deprived in the second year, and 37 % are still working but are no longer deprived. Of the working deprived, 5 % stop working but remain deprived in the second year. Among non-deprived workers, 3 % fall into deprivation while working.

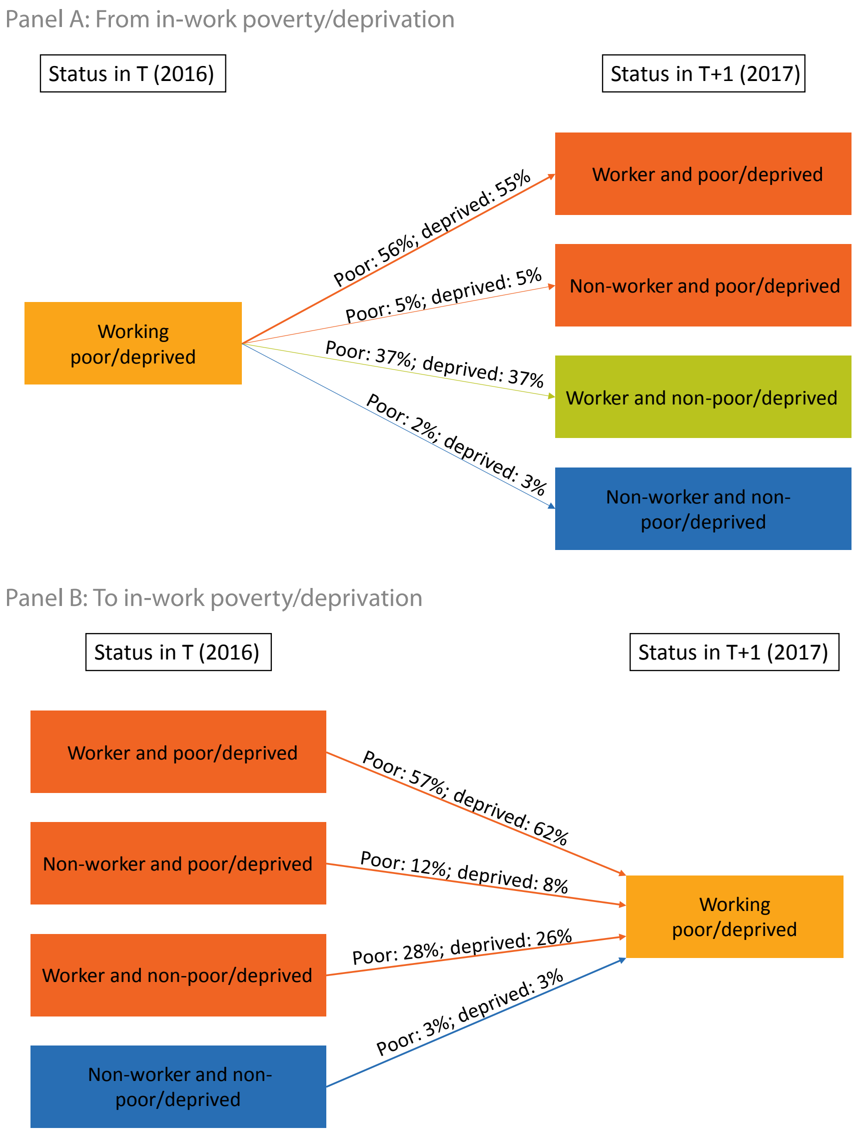
In the rest of the chapter, we focus our analysis on the distribution of individual situations preceding and following in-work poverty/deprivation, at both European and national levels.

Panel A of Figure 15.2 shows all the trajectories (in year T + 1) of those who are in-work poor/deprived in year T. A favourable trajectory is to move out of poverty/deprivation while staying in work (green arrow in Figure 15.2, Panel A). There are two possible negative trajectories: staying in-work poor/deprived or moving out of in-work poverty/deprivation because of an exit from work – not from poverty/deprivation (red arrows in Figure 15.2, Panel A). The last possible trajectory (moving out of in-work poverty/deprivation and being neither in work nor poor/deprived) is marginal (around 2 or 3 %) (blue arrow in Figure 15.2, Panel A).

All trajectories leading to in-work poverty/deprivation in year T + 1 are shown in Figure 15.2, Panel B. The distributions of three negative trajectories are of interest (red arrows).

- The first is the static one: of those individuals experiencing in-work poverty/deprivation on T + 1, most (57 % and 62 % respectively) were in the same situation the preceding year.
- The second one combines the trajectories of non-poor/deprived workers who entered poverty/deprivation while being in work. These workers make up respectively 28 % and 26 % of the in-work poor/deprived in T + 1 and account for two thirds of the entries into in-work poverty (28 % and 43 %) or in-work deprivation (26 % and 37 %), which is interesting from a policy point of view.
- The last category of interest is that of poor/deprived non-workers who find a job but remain in poverty/deprivation. These people make up respectively 12 % and 8 % of the working poor/deprived in T + 1.

Figure 15.2: Trajectories from/to in-work poverty/deprivation, 2016–2017
(%)



Note: Red (green) arrows show 'negative' ('positive') transitions that will be studied in Section 15.3. In Panel B, Belgium and Serbia are excluded because of missing values for some deprivation variables for at least 1 year, and Denmark, Norway and Sweden because their sample sizes are lower than 50 for some of the categories.

Reading note: Panel A shows that 37 % of working poor in T (2016) remained in work but managed to escape poverty. Panel B shows that, among the in-work poor in T + 1 (2017), 28 % were working and not poor in T.

Source: Author's computations, UDB 2019-1, weighted by RB062.

15.4.3. Year-to-year trajectories from in-work poverty/deprivation, by country

Figure 15.3, Panel A, shows that, in most countries, people who are working poor in the first year have a likelihood of between 45 % and 60 % of remaining working poor in the following year. This probability is, however, as high as 80 % in Romania and 70 % in Denmark, indicating a serious in-work poverty trap in both countries. In contrast, mobility appears relatively high in Hungary, Norway and Serbia, where fewer than 4 in 10 working poor in the first year remain working poor in the second year. In the next section, we will analyse whether this is due to specific socioeconomic characteristics of workers or to other factors.

Panel A of Figure 15.3 also confirms that in all countries the vast majority of year-to-year trajectories from in-work poverty are favourable ones: trajectories are most often due to a change in the AROP risk rather than a change in activity status on the labour market. This positive trajectory is shared by 57 % of the in-work poor in Hungary.

The proportion of workers who follow a negative trajectory remains significant in some countries: in Denmark, Latvia, Norway, Serbia and Spain, more than 10 % of the in-work poor move out of in-work poverty because of joblessness but remain poor.

These figures also show that the in-work poor who stop working are more likely to stay poor than to leave poverty in most countries (they are on average twice as likely to become non-workers and poor as non-workers and non-poor in the second year, the latter category accounting for less than 5 % in most countries). Finland is the only country where, surprisingly, poor workers are more likely to become non-workers and non-poor than to become non-workers and poor.

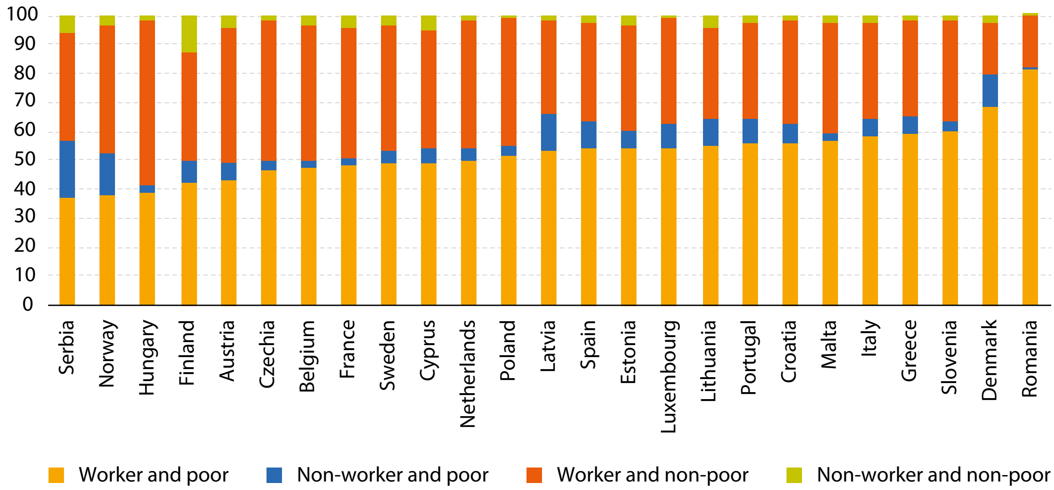
Figure 15.3, Panel B, shows a distribution of trajectories from in-work deprivation similar to that from in-work poverty; however, important country differences exist. In Bulgaria, Czechia, Greece, Latvia, Lithuania, Hungary and (even more) Romania, the working deprived have a likelihood of 50 % or more of remaining in this status in the second year, showing a strong in-work deprivation trap.

In this figure, the highest share of positive trajectories is experienced in Estonia, Spain, Italy, Cyprus, Malta, Austria, Slovenia and Finland: in these countries, more than one in two working deprived people continue to work but escape deprivation in the second year.

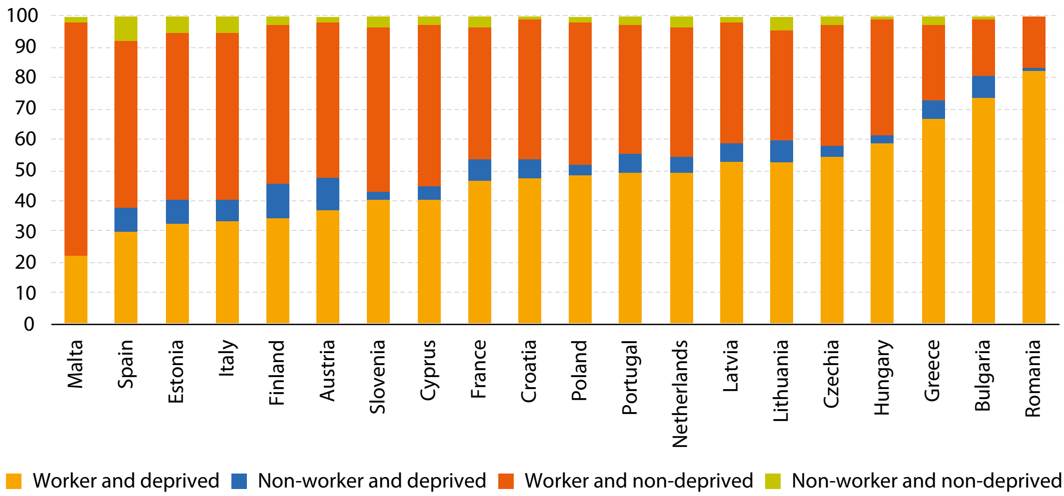
For those who stop working, Figure 15.3, Panel B, confirms that they are more likely to be deprived than to be non-deprived in the second year in all countries, except in Spain, Malta and Slovenia.

Figure 15.3: **Breakdown of the trajectories from in-work poverty/deprivation, by country, 2016–2017**
(%)

Panel A: Trajectories from in-work AROP



Panel B: Trajectories from in-work MSD



Note: Countries are sorted by increasing values of the proportion of 'Worker and poor' in Panel A, and of 'Worker and deprived' in Panel B. In Panel B, Belgium and Serbia are excluded because of missing deprivation variables for at least 1 year, and Denmark, Luxembourg, Norway and Sweden because their sample sizes are lower than 50 for some of the categories. The sample includes any person aged at least 16 whose self-declared economic activity status was either 'employed' or 'self-employed' for at least half of the income reference year, and who was poor (Panel A) or deprived (Panel B) in 2016.

Reading note: In Portugal, 49 % of the working deprived remain in this situation in the second year, although 42 % manage to escape deprivation and continue working.

Source: Author's computations, UDB 2019-1, weighted by RB062.

15.4.4. Year-to-year trajectories to in-work poverty/deprivation, by country

Table 15.3 shows the national variation in two types of trajectories for people moving into in-work poverty/deprivation:

- the proportion of non-poor/non-deprived workers who became poor/deprived, while remaining in work;
- the proportion of poor/deprived non-workers who found a job but remained in poverty/ deprivation.

The values in green highlight the best national situations, and those in red show the worst situations. Among those who were non-poor and in work (column 1), between 1 % (Finland) and 8 % (Luxembourg) moved to poverty, while staying in work. Among those who were poor and not in work the first year (column 2), between 2 % (Belgium, Denmark) and 15 % (Spain, Norway and Romania) found a job but remained in poverty.

Table 15.3 shows similar results for in-work deprivation. Workers have a low probability (< 2 %) of falling into deprivation in the Nordic countries, Austria, Luxembourg and Malta, and a high risk (6–8 %) of falling into deprivation in Greece, Cyprus, Latvia and Romania.

Among those deprived and not in work in the first year, between 4.5 % (Italy) and 30 % (Romania) found a job but remained in poverty.

It is also instructive to compare the colour gradient between the poverty and deprivation trajectories (columns 1 and 3; columns 2 and 4). Many countries are classified in more or less the same colour cluster, whatever the indicator used. There are, however, a few notable exceptions. In Luxembourg, workers face a high risk of income poverty (8.4 %) and a very low risk of deprivation (0.8 %). In Cyprus, the opposite is true. Workers face a high risk of entering into deprivation, but a low risk of falling into poverty. In Spain, the risk that poor non-workers will find a job but remain poor is one of the highest in the EU, although the risk of deprived non-workers finding a job and remaining deprived is intermediate. Greece is in the opposite situation. These results are driven by the national level of affluence, the level of wages, the dynamics of the labour market and the social protection of non-workers. In Luxembourg, for example, the general level of affluence protects people from deprivation but is associated with a high poverty threshold that low-wage workers or single earners may have difficulty reaching. In Romania, the low level of affluence, the share of low wages, the burden of large/complex families and the lack of social protection for non-workers lead to a high level of entry into both deprivation and poverty for both workers and non-workers.

Table 15.3: Selected trajectories to in-work poverty/deprivation, by country, 2016–2017
(%)

Country	Trajectories to in-work poverty		Trajectories to in-work deprivation	
	% of non-poor workers who moved into in-work poverty (1)	% of poor non-workers who moved into in-work poverty (2)	% of non-deprived workers who moved into in-work deprivation (3)	% of deprived non-workers who moved into in-work deprivation (4)
Finland	0.9	6.3	0.9	5.7
Czechia	1.6	7.3	1.5	8.2
Belgium	2.5	2.3	n/a	n/a
Denmark	1.0	2.4	1.8	n/a
Malta	2.5	3.0	1.7	7.3
Norway	2.3	14.2	0.4	n/a
Croatia	1.9	5.4	2.6	6.4
Netherlands	2.2	8.3	1.6	6.3
Slovenia	2.1	3.5	3.1	5.4
Sweden	2.0	12.2	0.3	n/a
France	2.6	8.5	2.4	6.0
Austria	3.0	9.3	1.3	7.9
Cyprus	1.8	8.8	6.4	9.9
Lithuania	3.5	8.9	3.5	8.5
Latvia	4.1	10.0	8.3	12.7
All countries	3.1	8.8	2.9	8.3
Estonia	3.3	13.1	3.2	13.3
Poland	3.6	7.0	2.2	9.9
Hungary	4.5	10.4	4.4	17.7
Portugal	3.2	8.0	3.8	8.3
Serbia	4.4	5.5	n/a	n/a
Italy	3.4	8.3	3.1	4.5
Greece	3.9	4.6	7.3	8.1
Spain	4.0	13.8	3.3	8.8
Luxembourg	8.4	9.5	0.8	n/a
Romania	3.4	15.0	6.2	29.1
Bulgaria	n/a	n/a	4.1	19.3

Note: n.a., not available (because of missing deprivation variables for at least 1 year (Belgium and Serbia), or sample size lower than 50 (Denmark, Luxembourg, Norway and Sweden)). Countries are sorted by increasing values of the annual in-work poverty rate. Workers include any person aged at least 16 whose self-declared economic activity status was either 'employed' or 'self-employed' for at least half of the income reference year, and non-workers include 'unemployed', 'student' or people 'fulfilling domestic tasks and care responsibilities'.

Reading note: In Finland, 1 % of the non-poor workers in 2016 moved into in-work poverty in 2017.

Source: Author's computations, UDB 2019-1, weighted by RB062.

15.5. Determinants of in-work poverty/deprivation trajectories

15.5.1. Econometric strategy

The descriptive analysis presented in the previous section highlighted the prevalence of the various types of trajectories. Here we seek to identify the determinants of the most policy-relevant positive and negative ones, namely:

1. for those in work and poor the first year, leaving work and remaining poor (negative trajectory);
2. for those in work and poor the first year, staying in work and escaping poverty (positive trajectory);
3. for those in work and deprived the first year, leaving work and remaining deprived (negative trajectory);
4. for those in work and deprived the first year, staying in work and escaping deprivation (positive trajectory);
5. for those in work and non-poor the first year, remaining in work and becoming poor (negative trajectory);
6. for those in work and non-deprived the first year, remaining in work and becoming deprived (negative trajectory).

To study trajectories 1 and 2, we will run a multinomial logistic regression (model a) to explore the factors associated with each of the four possible trajectories from in-work poverty, namely:

- staying in work and escaping poverty;
- staying in poverty while leaving work;
- escaping poverty and leaving work – not presented here, as this represents a minority of trajectories;
- remaining in in-work poverty (reference trajectory, so estimates are expressed in relation to it).

Similarly, to study trajectories 3 and 4, model b mirrors model a with respect to trajectories from in-work deprivation.

To study trajectory 5, we will run model c, which estimates the probability of:

- remaining in work and becoming poor;
- leaving work and becoming poor – not presented here, as this is not related to in-work poverty;
- leaving work and staying non-poor – not presented here, as this is not related to in-work poverty;
- remaining in-work non-poor (reference trajectory, so estimates are expressed in relation to it).

Finally, model d mirrors model c with respect to trajectories to in-work deprivation from being a non-deprived worker.

Because working (or not) is an individual attribute, the dependent variables reflect developments in the situations of individuals (e.g. staying in work and poor). All models are estimated at individual level.

15.5.2. Explanatory variables and sample

The risk factors identified in the analysis of in-work income poverty/deprivation dynamics (Hick and Lanau, 2018; Guttiérrez et al., 2011; Vandecasteele and Giesselmann, 2018; Halleröd et al., 2015; Crettaz and Bonoli, 2011; Grzegorzewska and Thévenot, 2014) are of three types: first, individual factors influencing the worker's capacity to generate earnings (work experience, educational attainment, duration of contract, self-assessed health limitations, country of birth, working part-time or full-time, occupational category, self-employment); second, factors related to the household size and its socio-economic composition (share of workers, share of dependent [166] children, receipt of social transfers

[166] Dependent children are individuals aged 0–17 years, and those aged 18–24 years if inactive and living with at least one parent.

by the household ([167])); third, changes in some of the previous variables. All individual factors and those influencing household size and socioeconomic composition are measured at the beginning of the transition (2016).

We focus on four kinds of year-to-year changes or 'trigger events': changes in the percentage of children living in the household, in the percentage of other workers living in the household ([168]), in the earnings of other household members and in the cumulative amount of social transfers. For the second and third triggers, only variations of 10 % or more in the net amounts received are recorded as changes, to avoid giving undeserved weight to slight variations. Year-to-year increases and decreases are considered separately.

These triggers reflect possibly complex events that are contemporaneous with a poverty/deprivation transition, and this makes them difficult to analyse. To illustrate, consider that an increase in the percentage of children living in the household is observed to be associated with a heightened risk of entry into poverty. Yet the increase in the percentage of children could itself result from the separation/divorce of adult partners and the departure of an adult from the household. Another telling example is the ambiguous impact on poverty/deprivation dynamics to be expected from the increase in the earnings of other members of the household: if the increase in earnings stands for a secondary earner in the household increasing their earnings while the main earner maintains their income, then the household will be better off; but, if the increase in others' earnings reflects the attempts of a secondary earner to compensate for a loss of income by the main earner, then the household may well be worse off after the change. Therefore, trigger events should not be given a causal interpretation.

To account for differences between self-employed people and employees, we use a dummy variable distinguishing households that include self-employed people from those that do not.

We included country dummies (estimating fixed effects for each country).

We did not include in the model the respondent's earning variation or the variation in the total number of workers per household, owing to their tautological relation with the dependent variables: by definition, when a poor worker becomes a poor non-worker or non-poor non-worker, the total number of workers in the household diminishes by one and the total earning of the worker decreases by 100 %.

Some important predictors, such as the country of birth of the worker and the number of hours worked, are omitted because the information is missing in the longitudinal survey. This may affect the quality of our econometric estimation, as these two variables are usually recognised in the literature as important explanatory variables of cross-sectional in-work poverty in Europe (see for example Peña-Casas et al., 2019). Furthermore, the number and duration of past periods in poverty/deprivation are largely unknown ([169]) but they are likely to influence the probability of the transitions we study. Finally, it is worth keeping in mind that some variables are related to the survey year (duration of working contract) and others are related to the income reference period (working status, part-time or full-time work).

We used the 'pooled data set' (see Section 15.3). In the estimations regarding trajectories from in-work poverty/deprivation, people who were in work in 2016 and left the labour market in 2017 because of retirement, permanent disabilities or compulsory military or community service are excluded.

([167]) A dummy variable indicates if the household receives any of the following social transfers: family-/children- and education-related allowances, benefits aimed at combating social exclusion, housing allowances, unemployment, survival, sickness or disability benefits. Old-age benefits are not included.

([168]) We determine the year-to-year variation in the percentage of workers living in the household after excluding the survey respondent. This is done to prevent a mechanical decrease in the value of this predictor for all households where a worker leaves work from one year to the next (such an explanatory variable would have a tautological relationship with the dependent variable). However, the static variable describing the percentage of workers living in the household (in 2016) considers all workers living in the household.

([169]) EU-SILC's longitudinal component is too short (4 years) and the sample size of the balanced 4-year panel too small (at most one quarter of the initial sample) to take this aspect into account in our estimations.

15.5.3. Results

Table 15.4 shows a selection of the findings drawn from the econometric analysis described in Section 15.5.1. The full set of results is available on demand.

The left part of the table presents the impact of the independent variables on the probability of some trajectories from in-work poverty/deprivation. The right part of the table shows results for some of the trajectories experienced by those who were in work and non-poor/non-deprived the first year and become working poor/deprived the second year.

For ease of interpretation, the relative risk ratios (i.e. the exponentiated regression coefficients) are presented. They measure the probability of experiencing one of the trajectories, compared with the reference situation, for a unit change in the independent variable considered, all else being equal (see the reading note under Table 15.4 for an example). Dummy variables are interpreted in relation to the reference category of the independent variable. Only the risk ratios that are significantly different from 1 at the 0.05 threshold are shown.

The two unfavourable transitions of leaving work but remaining poor or deprived respectively (columns 1 and 2), are most associated with having a temporary work contract in year T and with the household experiencing a year-to-year increase in social benefits. Both effects are expected, but the increase in social benefits received is, however, a consequence rather than a cause of losing work [170]. Having less than 5 years of work experience also increases the likelihood of these transitions. Larger households with the same proportion of workers and of children are more shielded from these negative transitions: for example, if a single working parent lives with one child, and a dual-earner couple lives with two children (where the proportions of children and workers are identical), the larger household is less likely to lose work and remain poor/deprived.

A lower risk of poor workers becoming workless and staying poor is associated with a year-to-year increase in the share of other workers in the household, as well as with not suffering from health limitations. In turn, the risk of remaining deprived and becoming out of work correlates with a decrease in the earnings of other household members.

Movements out of poverty/deprivation by leaving work are associated with an increase in earnings of other household members, which may seem counterintuitive. This finding reflects the fact that in many households, when a worker loses/leaves employment, other members of the household take up work, or work (and earn) more than they had previously, but these efforts fail to compensate for the lost earnings.

The favourable transitions of leaving poverty or deprivation while staying in work (columns 3 and 4) are associated with different trigger events. The likelihood of workers leaving income poverty is raised the most by a year-to-year increase in the earnings of other members of the household. A year-to-year increase in social benefits also enhances the chances of becoming non-poor, as does a year-to-year increase in the share of other workers. Mirroring this, a year-to-year increase in the share of children reduces the chances of workers' households becoming non-poor. Such an impact is expected, because an increase in the share of children can be triggered either by the birth of children, which raises the needs of the household, or by the departure of an adult (or more than one), which is likely to reduce the resources available to the household.

None of the above changes is found to be associated with workers' move out of deprivation in our model. This may be due to the short time frame (only 1 year lag) of our analysis. Indeed, it is well known that deprivation is influenced by variations in permanent income, rather than current income. It may take a few years for a variation in current income to have an impact on deprivation, depending on the household's capacity to save, or its debt, as well as on the variations in current income in the other years.

Individual characteristics mostly have a similar association with moving out of poverty/deprivation:

(170) In all EU Member States, former workers receive some form of replacement income after they stop work (e.g. unemployment benefits at the end of a fixed-term contract or following firing, or parental leave).

having a medium/higher education and a medium/higher occupational category increases the chances of leaving poverty/deprivation; working part-time decreases them. Households having a higher share of workers are more likely to become non-poor/non-deprived, as are households composed of at least two persons. Having long work experience and the absence of self-employed people in the household only matter for moving out of income poverty, whereas suffering from no health limitations only increases the chances of leaving deprivation.

These last two results confirm findings from the existing literature. The fact that an association is found between self-employment and some poverty-related trajectories but not with the corresponding deprivation trajectories may be due to the difficulties of accurately recording self-employment income in surveys such as EU-SILC (see Chapter 19 of this volume). The higher risk of deprivation of people suffering from health problems can be explained by health costs, which have an impact on deprivation and not on the poverty risk.

The likelihood of workers' becoming poor (column 5) is raised most by a higher share of children in the initial year and by the year-to-year decrease in the earnings of other household members. A year-to-year decrease in social benefits received, a year-to-year increase in the share of children, having short work experience, working part-time and having a fixed-term contract also raise the prospects of this negative transition occurring. A household size greater than one (keeping the proportion of workers to children constant), a higher share of workers, the absence of self-employment, having medium/high education, being in a high occupational category and a year-to-year increase in the earning of others also protect against this negative outcome.

The chances of workers becoming in-work deprived (column 6) are slightly elevated by three triggers: a year-on-year drop in the share of children, a decrease in the share of other workers in the household and a decrease in the earnings of others. Having a fixed-term contract, working only part-time and receiving social transfers also increase the likelihood of this negative transition. Becoming deprived while staying in work is made less likely by households being larger and having a higher share of workers, and by workers having medium/high education, a medium/high occupation and good health.

Table 15.4 also highlights some large national differences not explained by the individual or household characteristics included in our models. This suggests that other country-specific characteristics shield workers from moving into in-work poverty/deprivation or facilitate their move out of in-work poverty/deprivation. These country-specific characteristics relate to (1) national labour market institutions, such as employment protection regulations and wage-bargaining arrangements, and national labour market characteristics, such as the prevalence of low pay, union density and compressed wage distribution; (2) welfare state regulations, such as the selectivity and generosity of social transfers or the public provision of childcare allowing parents to combine caregiving with employment; and (3) the sociodemographic composition of each country, for example the share of dual-earner households or of single parents (see Lohmann and Andreß, 2008, for an extensive discussion). When the impact of explanatory variables included in our models is controlled for, the following variability in national patterns emerges ([171]).

National characteristics are associated with a lower likelihood of experiencing 'bad' transitions out of in-work poverty (that is moving out of in-work poverty by losing work) in Belgium, Denmark, France, Hungary, Poland, Romania and Slovenia. The chances of leaving poverty by a 'good' transition (that is remaining in work) are enhanced by national characteristics in Belgium and Hungary, and diminished in Denmark, Estonia, Romania and Slovenia.

The risk of non-poor workers moving into in-work poverty is lowered by national characteristics in Estonia, Latvia, Luxembourg, Hungary and Serbia, and it is increased by national characteristics in Czechia, Denmark, Cyprus, the Netherlands, Finland and Sweden.

([171]) The reference country is Portugal. It was chosen because its cross-sectional in-work poverty rates and in-work deprivation rates, as well as its transition rates into and out of in-work poverty/deprivation, are moderate in comparison with those of other countries included in the analysis.

Globally, Denmark is characterised by a very low probability of workers moving into poverty, but those who do move are trapped. The opposite situation is observed in Serbia.

National characteristics reduce the likelihood of workers moving into deprivation in Czechia, Denmark, France, Italy, Luxembourg, Malta, the Netherlands, Austria, Finland and Sweden. They increase the probability of workers moving into in-work deprivation in Greece, Cyprus, Latvia, Hungary and Romania.

The likelihood of leaving in-work deprivation by losing work ('bad' transition) is lowered by national characteristics in France, Hungary, Malta, Poland, Romania and Sweden. The probability of leaving deprivation while staying in work ('good' transition) is reinforced by national characteristics in Estonia, Spain, Italy and Malta, while it is weakened in Czechia, Greece, Latvia, Lithuania, Hungary and Romania.

Table 15.4: Relative risk ratios, where these are significantly different from 1 ($p < 0.05$), for selected trajectories to/from in-work poverty/deprivation – results from four multinomial logistic regressions, 2016–2017

	Trajectories from in-work poverty/deprivation:				Trajectories to poverty/ deprivation:	
	RRR of leaving work and remaining poor versus remaining in-work poor (model a) (1)	RRR of leaving work and remaining deprived versus remaining in-work deprived (model b) (2)	RRR of leaving poverty and remaining at work versus remaining in-work poor (model a) (3)	RRR of leaving deprivation and remaining at work versus remaining in-work deprived (model b) (4)	RRR of becoming in-work poor versus remaining in-work non-poor (model c) (5)	RRR of becoming in-work deprived versus remaining in-work non-deprived (model d) (6)
Educational attainment (ref.: low, ISCED 0–2)						
Medium (ISCED 3–4)			1.4	1.4	0.7	0.7
High (ISCED 5+)			1.8	1.5	0.4	0.5
Work experience (years) (ref.: 10–19)						
< 5	1.7	1.8			2.1	
5–9					1.3	
> 20			0.8			
Duration of contract (ref.: permanent)						
Temporary	2.9	2.9			1.7	1.4
Working time (ref.: full-time, 30 h/week or more)						
Part-time			0.7	0.7	2.1	1.6
Occupational category (ref.: low, ISCO 8–9)						
Medium (ISCO 4–7)			1.2	1.3		0.7
High (ISCO 1–3)			1.6	1.8	0.4	0.3
Health limitations (ref.: strongly limited and limited)						
Not limited	0.5			1.3		0.6
Household size (ref.: single person)						
2 persons	0.4		1.7	2.3	0.2	0.3

	Trajectories from in-work poverty/deprivation:				Trajectories to poverty/ deprivation:	
	RRR of leaving work and remaining poor versus remaining in-work poor (model a) (1)	RRR of leaving work and remaining deprived versus remaining in-work deprived (model b) (2)	RRR of leaving poverty and remaining at work versus remaining in-work poor (model a) (3)	RRR of leaving deprivation and remaining at work versus remaining in-work deprived (model b) (4)	RRR of becoming in-work poor versus remaining in-work non-poor (model c) (5)	RRR of becoming in-work deprived versus remaining in-work non-deprived (model d) (6)
3 persons	0.3	0.3		2.1	0.0	0.2
> 3 persons	0.2	0.3		2.8	0.0	0.1
Share of children in the household						
Share of children					5.3	
Share of workers in the household						
Share of workers			2.3	2.7	0.0	0.2
Self-employed in the household (ref.: yes)						
No			1.7		0.2	
The household received social benefits (ref.: no)						
Yes						1.5
Variation in the share of dependent children living in the household (ref.: stable)						
Decrease						1.4
Increase			0.5		1.8	
Variation in the share of other workers living in the household (ref.: stable)						
Decrease						1.4
Increase	0.5		1.6			
Variation in earnings of other members living in the household (ref.: stable)						
Decrease		1.7		1.4	4.5	1.3
Increase	2.3	1.9	3.9		0.5	
Variation in social benefits (ref.: stable)						
Decrease				1.5	2.2	
Increase	2.9	3.1	1.9			
Country (ref.: Portugal)						
Belgium	0.3	n/a	2.0	n/a		n/a
Czechia				0.6	0.6	0.5
Denmark	0.0		0.3		0.2	0.4
Estonia			0.7	1.7	1.4	
Greece				0.4		2.7
Spain				2.3		
France	0.1	0.2				0.7
Croatia						
Italy				2.2		0.8
Cyprus					0.6	2.2
Latvia				0.6	1.8	2.9
Lithuania				0.6		
Luxembourg					3.9	0.2

	Trajectories from in-work poverty/deprivation:				Trajectories to poverty/ deprivation:	
	RRR of leaving work and remaining poor versus remaining in-work poor (model a) (1)	**RRR of leaving work and remaining deprived versus remaining in-work deprived (model b) (2)**	**RRR of leaving poverty and remaining at work versus remaining in-work poor (model a) (3)**	**RRR of leaving deprivation and remaining at work versus remaining in-work deprived (model b) (4)**	**RRR of becoming in-work poor versus remaining in-work non-poor (model c) (5)**	**RRR of becoming in-work deprived versus remaining in-work non-deprived (model d) (6)**
Hungary	0.2	0.4	1.5	0.6	1.7	1.6
Malta		0.0		3.9		0.5
Netherlands					0.3	0.3
Austria						0.4
Poland	0.3	0.4				
Romania	0.1	0.1	0.4	0.2		2.1
Slovenia	0.1		0.6			
Finland					0.2	0.2
Sweden		0.0			0.4	0.1
Norway		n/a		n/a		n/a
Serbia	5.9	n/a	1.7	n/a	1.5	n/a
Number of observations	*10 034*	*11 316*	*10 034*	*11 316*	*98 846*	*88 679*

Note: n.a.: not available; RRR, relative risk ratio.

Workers include any person aged at least 16 whose self-declared economic activity status was either 'employed' or 'self-employed' for at least half of the income reference year, and non-workers include 'unemployed', 'student' or people 'fulfilling domestic tasks and care responsibilities'.

Reading note: The fact that the relative risk ratio of becoming a 'non-poor worker' is 1.8 for more highly educated workers means that the likelihood that more highly educated workers will exit income poverty while remaining in work, rather than remaining in-work poor, is almost twice as high as for less-educated workers.

Source: Author's computations, UDB 2019-1, weighted by RB062.

15.6. Conclusion

At EU level, a significant share of workers are AROP (1 out of 11) or suffer from MSD (1 out of 12). Although workers are more protected against being AROP and MSD than the overall population, they account for a particularly worrying share of those AROP or suffering from MSD.

However, only sparse information exists at EU level about the dynamics of in-work poverty/deprivation. These dynamics are more complex than the poverty dynamics for the general population, because movements into and out of in-work poverty/deprivation are generated both by changes in individuals' employment status and by changes in households' poverty/deprivation situation. The share of those who move into and out of working poverty/deprivation, and the reasons why, are largely unknown. The aim of this chapter is to begin filling this gap.

The chapter highlights that just over half of the working poor/deprived remain working poor/deprived a year later. Almost 40 % manage to escape poverty/deprivation and remain in work, which is a favourable transition. However, 5 % of the working poor/deprived follow an unfavourable path out of in-work poverty/deprivation, by leaving work while remaining poor/deprived.

The analysis of trajectories into in-work poverty/deprivation shows that a non-negligible share of persons move into poverty/deprivation while working: around one quarter of those in-work poor/deprived in the second year were already in work and not poor/deprived the previous year, which is a troubling figure.

The chapter also seeks to assess econometrically the impact of individual factors (e.g. work experience, educational attainment, part-time work), household characteristics (e.g. share of dependent children, share of workers) and trigger events (changes in the composition of the household, changes in earnings and in social transfers) on the likelihood of six trajectories: movements of workers into in-work poverty, movements out of in-work poverty by leaving work, movements out of in-work poverty while staying in work, and the corresponding three trajectories with respect to in-work deprivation.

The static individual and household characteristics mostly have the expected impacts and are similarly associated with transitions into / out of in-work poverty/deprivation. Having medium/high educational attainment and being in a medium/high occupational category decrease the chances of moving into in-work poverty/deprivation and increase the likelihood of moving out of in-work poverty/deprivation while keeping work. The opposite is true of part-time work. Having a temporary contract enhances both the chances of workers moving into poverty/deprivation and those of leaving work while remaining poor/deprived.

The presence of self-employed people in the household diminishes the chances of moving out of poverty and increases those of moving into in-work poverty, yet does not affect the corresponding deprivation trajectories. This may highlight a difficulty in accurately measuring self-employment income in surveys.

The presence of health limitations has no impact on the risk of workers falling into / moving out of poverty while staying in work, but has an impact on the deprivation trajectories. A plausible explanation is that the health costs reduce the share of current income that is available for consumption, and this is better approached by the deprivation indicator. Health problems also have an impact on the likelihood of stopping working but remaining poor for those in work.

Our analysis also shows that, although the rates of movement into and out of in-work poverty/deprivation are similar, the trigger events linked with these in-work poverty/deprivation trajectories are somewhat different. For instance, a year-to-year increase in social benefits received by the household is associated with an increased likelihood of both moving out of in-work poverty and moving out of in-work deprivation when work is lost, but, for workers who remain at work, this trigger only improves the chances of escaping poverty and bears no significant association with the corresponding deprivation trajectory. A year-to-year decrease in social benefits is only linked to higher chances of entering poverty, not deprivation. Similarly, a year-to-year increase in the share of children living in the household augments the chances of workers entering in-work poverty and diminishes the likelihood of escaping poverty while keeping work, but it does not affect the corresponding deprivation trajectories. Most probably the absence of a statistically significant association with deprivation-related trajectories can be explained by the fact that changes in current income have a lagged relationship with deprivation, which is more influenced by permanent income than by current income, as the existing literature suggests.

These results highlight the importance of complementing the income measure with the deprivation measure when assessing the dynamics of in-work poverty and deprivation.

Caution is, however, needed in the interpretation of the impact of triggers: triggers should be understood not as causes of transitions, but rather as events that occur together with the transitions, whose impact reflects the net result of the changes in the circumstances of the household and of adjustments it made.

Our analyses also show that large country-to-country differences in the likelihood of trajectories related to in-work poverty/deprivation are not explained by the sociodemographic and labour variables included in our models. Differences in national labour market institutions and processes (e.g.

compression of wage distribution) or in the provision of welfare support may help explain these differences between countries. This calls for further econometric work using multilevel models.

Finally, our results have policy relevance. From a policy perspective, the fact that having a temporary work contract in the initial year and experiencing a year-to-year increase in social benefits raise the likelihood of households remaining poor/deprived after losing work suggests the social transfers targeted at workless households are insufficient to lift out of hardship those households that lose their market earnings. Social transfers also play an essential role in shielding the working population from poverty: a year-to-year decrease in social transfers is found to increase workers' chances of falling into poverty, while a year-to-year increase in social transfers is found to enhance the chances of leaving poverty while staying in work.

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16

Chronic multidimensional poverty in Europe

Sabina Alkire and Mauricio Apablaza, with Anne-Catherine Guio (172)

16.1. Introduction

In 2021, interest in understanding and redressing the social exclusion of individuals and groups remains powerful and unabated. This chapter seeks to deepen understanding of potential measures of poverty and social exclusion in the EU. It uses the EU-SILC longitudinal data set to construct two types of multidimensional poverty indicators for 2014–2017 to study the individual persistence/volatility of multidimensional poverty over that period. The first indicator is based on the three AROPE dimensions. The second indicator is an extended measure that includes other salient dimensions of social exclusion: education, health and housing.

The next section briefly presents the literature on which this chapter builds. Section 16.3 presents the method and the data used. The results for each indicator are detailed in Sections 16.4 and 16.5. The last section concludes.

16.2. Literature review

Earlier work has summarised the extensive literature using counting-based measures of multidimensional poverty, deprivation and social exclusion in Europe to complement monetary measures, and argued for ongoing consideration of both kinds of measures (Nolan and Whelan, 2011; Alkire et al., 2015; Alkire and Apablaza, 2017; Atkinson, 2019).

Measurement methodologies for extending multidimensional measures to longitudinal data have developed (Alkire et al., 2017, and the references cited therein), and dozens of developing countries have now launched official statistics using counting measures (173). This chapter builds upon those, so, rather than repeating them, it cites relevant studies in the course of the analysis.

16.3. Methods and data

We use the Alkire–Foster approach (Alkire and Foster, 2011) to build and analyse two different multidimensional poverty indicators (MPIs). Both are inspired by the AROPE indicator; however, they differ in terms of construction and aggregation. The two proposed measures are not directly comparable, owing to differences in the populations of reference.

The first measure comprises three EU social indicators: AROP, QJ and the MSD agreed at EU level in 2017 (see Guio et al., 2016). The composition of this first MPI is similar to AROPE, except that we replaced the SMD indicator by the newly agreed (non-severe) MSD indicator. This first indicator is

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(173) As this is a fast-moving area, the most recent information on national multidimensional poverty indicators is available from the website of the Multinational Poverty Peer Network (www.mppn.org).

computed for the whole population aged less than 60 (i.e. including children). The second MPI also includes indicators pertaining to adult education, household housing conditions and adult health. This second indicator is only available for the adult population (aged 16 and above).

The associations between indicators are explored for the different years and indicator definitions. The structure of the multidimensional indicators follows Alkire and Apablaza (2017) [174]. Table 16.1 provides detailed information regarding the definition and weights of each indicator by dimension.

In the chapter, we observe how the level and composition of these two MPIs change over time from 2014 to 2017, and how the duration of deprivation in each dimension varies. Country patterns are noted as well as regular patterns across countries. Following Alkire et al. (2017), information on poverty dynamics is summarised using a chronic multidimensional poverty measure that reflects the persistence of multidimensional poverty over time. The dynamics of the two MPIs are analysed separately first. Then, using only the population aged 16 or more, countries are compared and the potential value added from incorporating additional dimensions is considered.

16.3.1. Chronic multidimensional poverty measure

Alkire et al. (2017) propose a novel counting procedure to measure chronic multidimensional poverty based on the Alkire–Foster and duration approaches. Let x_{ij}^t stand for the quantity of attribute j possessed by person i in period t. Person i is regarded as deprived with respect to dimension j in period t if $x_{ij}^t < z_j$ and $g_{ij}^t(0)$ takes the value 1. If the individual is not deprived $(x_{ij}^t \geq z_j)$, $g_{ij}^t(0)$, $g_{ij}^t(0)$ takes the value 0.

$$c_i^t = \sum_{j=1}^{d} w_j g_{ij}^t(0)$$

c_i^t gives the weighted sum of deprivations for person i in period t. The identification of the chronically multidimensionally poor is defined by $\rho_i(k;\tau) = 1$ if and only if individual i is chronically multidimensionally poor, according to deprivation cut-off (z), weight (w), poverty (k) and duration cut-off (τ).

$$M_c^0 = \frac{1}{N}\sum_{i=1}^{N} \rho_i(k;\tau)\,\frac{1}{T}\sum_{t=1}^{T} c_i^t = H^c \times A^c \times D^c$$

M_c^0 is an extension of the Alkire–Foster multidimensional poverty index to chronic poverty and is an extension of the Foster–Greer–Thorbecke (1984) index into multidimensional space–time. M_c^0 can be expressed in terms of intuitive partial indices that convey meaningful information on different features of a society's experience of chronic multidimensional poverty. H^c is the headcount ratio of chronic multidimensional poverty, the percentage of the population who are chronically multidimensionally poor according to k and τ. A^c is the average intensity of poverty among the chronically multidimensionally poor, or the share of weighted deprivations that chronically poor people experience in the periods when they are multidimensionally poor. D^c reflects the average duration of poverty among the chronically multidimensionally poor, that is, the average share of periods in which they experience multidimensional poverty.

16.3.2. Structure of the two multidimensional poverty indexes

Table 16.1 presents the indicators for each dimension included and the deprivation cut-offs for the two multidimensional poverty measures used in this chapter. Justification of the indicators is provided by Alkire and Apablaza (2017).

(174) Environmental measures (noise, pollution and crime) and unmet medical needs were also excluded because of data unavailability.

Table 16.1: Dimensions, indicators, deprivation cut-offs and weights

Dimension	Variable (weight)	Respondent is not deprived if:
Income	AROP (in MPI1, 1/3; in MPI2, 1/6)	The respondent lives in a household whose equivalised disposable income is above 60 % of the national equivalised median income.
Employment	QJ (in MPI1, 1/3; in MPI2, 1/6)	The respondent lives in a household where the ratio of the total number of months that all household members aged 16–59 have worked during the income reference year to the total number of months the same household members theoretically could have worked in the same period is higher than 0.2. Individuals aged 60+ were considered non-deprived.
Material and social deprivation	MSD (in MPI1, 1/3; in MPI2, 1/6)	The respondent has at least 8 of the 13 MSD items.
Education	Education (in MPI1, 0; in MPI2, 1/6)	The respondent has completed upper secondary education.
Housing	Quality of the dwelling (in MPI1, 0; in MPI2, 1/18)	The respondent lives in a dwelling with no leaking roof, damp walls or rot in the window frames or floor.
	Bathroom (in MPI1, 0; in MPI2, 1/18)	The respondent lives in a dwelling with an appropriate bath or shower and flushing toilet.
	Overcrowding (in MPI1, 0; in MPI2, 1/18)	The respondent lives in a house without overcrowding. According to Eurostat standards, a person is deprived if the household does not have at its disposal a minimum of rooms equal to (1) one room for the household; (2) one room per couple in the household; (3) one room for each single person aged 18 and more; (4) one room per pair of single people of the same sex between 12 and 17 years of age; (5) one room for each single person between 12 and 17 years of age and not included in the previous category; (6) one room per pair of children under 12 years of age.
Health	Self-reported health (in MPI1, 0; in MPI2, 1/18)	The respondent considers their own health fair or above.
	Chronic illness (in MPI1, 0; in MPI2, 1/18)	The respondent has no chronic illness or long-term health condition.
	Morbidity (in MPI1, 0; in MPI2, 1/18)	The respondent reports no limitation due to health problems.

Note: MPI1, first multidimensional poverty indicator; MPI2, extended multidimensional poverty indicator.

16.3.3. Data

We use the 2014–2017 EU-SILC longitudinal data. The data set includes 26 countries, namely all Member States except Germany, Ireland and Slovakia, and two non-EU EU-SILC countries (Norway and Serbia). However, Serbia (2016), Belgium (2015–2016), Luxemburg (2015) and Norway (2016) are excluded from our analysis because of substantial non-response for the MSD indicator. As Table 16.2 shows, 93 572 individuals in 22 countries have full information in all years for the three dimensions of the first multidimensional poverty indicator (MPI1). The number of individuals aged 16+ with full information is 66 333 when all six dimensions and 10 indicators are considered (Table 16.2).

The main difference in the number of observations between the measures is the age restrictions (58 % or 15 509 individuals). When both measures are compared only including individuals over 15, the fall in sample size is driven by the health dimension. The three health indicators are available for only 66 723 to 69 062 respondents. Whereas all dwelling quality indicators are available for over 79 089 respondents, education is available for 77 041 respondents (271 individuals were excluded owing to inconsistent data). If any person lacks data in any of the 10 indicators, they are dropped from the sample for the second measure ([175]).

([175]) The extent of dropout from the sample due to attrition and non-response means that results are illustrative; for policy use, further assessments would be required to ascertain if the dropout introduced bias and to correct it.

Table 16.2: Number of observations with full information, longitudinal data, by country, 2014–2017

Country	Three dimensions (age 0+)		Six dimensions (age 16+)	
	Observations available for all years	Contribution of country (%)	Observations available for all years	Contribution of country (%)
Austria	2 599	2.80	2 055	3.10
Bulgaria	6 924	7.40	6 015	9.10
Cyprus	2 657	2.80	2 174	3.30
Czechia	3 934	4.20	2 141	3.20
Denmark	2 101	2.20	938	1.40
Estonia	3 128	3.30	1 440	2.20
Greece	5 358	5.70	4 512	6.80
Spain	5 890	6.30	4 857	7.30
Finland	4 713	5.00	1 908	2.90
France	10 735	11.50	8 258	12.50
Croatia	2 628	2.80	2 173	3.30
Hungary	3 226	3.50	2 631	4.00
Italy	8 027	8.60	6 001	9.10
Lithuania	2 698	2.90	1 346	2.00
Latvia	2 480	2.70	2 073	3.10
Malta	2 263	2.40	1 901	2.90
Netherlands	4 162	4.50	1 814	2.70
Poland	6 323	6.80	5 048	7.60
Portugal	3 743	4.00	3 127	4.70
Romania	4 079	4.40	3 672	5.60
Sweden	1 781	1.90	761	1.20
Slovenia	4 123	4.40	1 488	2.30
Total	93 572	100.00	66 333	100.00

Reading note: This descriptive table provides the number of observations used for each country's illustrative chronic multidimensional poverty measure, and the percentage of the population that each country contributes according to each measure (note that MPI2 only covers adults aged 16–59, although MPI1 covers people aged under 59, including children).

Source: Authors' computations, UDB 2019-1, unweighted number.

Table 16.3 shows the percentage of people who are deprived in each indicator. For the first three indicators, percentages were calculated using the full sample. The other indicators use the sample of adults for which the indicators are available. Deprivations in education are the highest of all indicators, followed by deprivations in chronic illness and morbidity. The steepest reductions between 2014 and 2017 are in dwelling quality problems (30 %) and material and social deprivation (28 %). In total, six indicators had statistically significant decreases between 2014 and 2017. By contrast, indicators of chronic illness and morbidity experienced a significant increment between 2014 and 2017.

Table 16.3: Percentage of people deprived in each year (95 % confidence interval), pooled data set, 2014–2017
(%)

Indicator	2014	2015	2016	2017
AROP (*)	16.9 (16.7–17.2)	16.7 (16.5–16.9)	16.9 (16.6–17.1)	16.1 (15.9–16.3)
QJ (*)	8.3 (8.1–8.5)	7.7 (7.5–7.9)	7.4 (7.2–7.6)	6.6 (6.4–6.8)
MSD (*)	18.9 (18.6–19.1)	17.5 (17.3–17.8)	15.7 (15.5–16)	13.7 (13.5–13.9)
Education (*)	35.4 (35–35.7)	33.9 (33.5–34.2)	32.7 (32.3–33)	32.1 (31.7–32.4)
Dwelling quality (*)	16.9 (16.6–17.2)	15.3 (15–15.6)	15 (14.7–15.3)	11.8 (11.5–12)
Bathroom	4.2 (4–4.3)	4.2 (4–4.3)	4 (3.9–4.2)	3.9 (3.7–4)
Overcrowding (*)	19.2 (18.9–19.5)	18.9 (18.6–19.2)	18.3 (18–18.6)	17.9 (17.6–18.2)
Self-reported health	9.6 (9.3–9.8)	9.6 (9.4–9.8)	9 (8.7–9.2)	9.2 (8.9–9.4)
Chronic illness	30.7 (30.3–31)	32 (31.7–32.4)	31.2 (30.9–31.6)	32.3 (31.9–32.6)
Morbidity	25 (24.7–25.3)	26.7 (26.3–27)	25.3 (25–25.7)	26.6 (26.2–26.9)

Note: (*) These indicators had significant reductions between 2014 and 2017.

Reading note: This table provides the percentage of people across all countries considered who are deprived in each indicator each year. In brackets are the confidence intervals at 95 %.

Source: Authors' computations, UDB 2019-1, weighted by RB064 that is available for 93 277 and 66 151 observations in measures 1 and 2 respectively.

16.3.4. Duration of deprivation in each dimension

Table 16.4 shows measures of the persistence of deprivations in each dimension. The first column reports the percentage of the population who were not deprived in the indicator in any period. The second and third columns report the percentages of persons whose deprivation status changed between the first period (2014) and the last one (2017). The fourth column represents those individuals who were always deprived in all four periods. The fifth column reflects persons whose starting and ending deprivation conditions are the same, but whose conditions changed in one or both intermediate periods (which we label 'churn'). Among the three indicators taken into account in the first measure (MPI1), just over one quarter of persons who were deprived in at least 1 year were deprived throughout 2014–2017 for each indicator (AROP, QJ, MSD). Education (90.1 %) is a stock indicator, because it measures the highest ISCED level attained, which does not change for the majority of people when completed. Among the other indicators, the deprivations that are most likely to be chronic are the lack of a bathroom and problems of overcrowding, followed by chronic illness. Those that appear to be most transitory are self-reported health and quality of the dwelling. This analysis raises questions about the extent to which chronic deprivations in the indicators overlap.

Table 16.4: Percentages of people with different deprivation sequences, pooled data set, 2014–2017

Indicator	Never deprived (%)	Improve (%)	Worsen (%)	Always deprived (%)	Churn (%)	Share of ever deprived who are always deprived (%)	Observations with data and weights in all four periods
AROP	73.5	6.7	5.9	8.1	5.8	30.6	93 277
QJ	87.3	4.3	2.6	3.4	2.5	26.8	93 277
MSD	73.0	9.0	3.8	7.6	6.6	28.1	93 277
Education	64.6	3.5	0.0	31.9	0.0	90.1	66 151
Dwelling quality	70.2	10.8	5.7	3.9	9.5	13.1	66 151
Bathroom	95.4	0.6	0.3	3.6	0.2	78.3	66 151
Overcrowding	77.0	4.3	3.0	14.5	1.3	63.0	66 151
Self-reported health	82.6	4.7	4.3	3.4	5.0	19.5	66 151
Chronic illness	51.4	9.6	11.1	16.5	11.4	34.0	66 151
Morbidity	56.6	9.1	10.7	11.8	11.7	27.2	66 151

Reading note: 74 % of people were not AROP in any period, although 6–7 % changed their poverty status between the first period (2014) and the last one (2017). The proportion of individuals who were always AROP in all four periods was 8.1 %, although 5.8 % were poor during the first and last years but not during the second and/or third. In total, more than 30 % of the people who had at least one episode AROP were poor throughout the 4 years.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

16.4. Dynamics of the first multidimensional poverty indicator

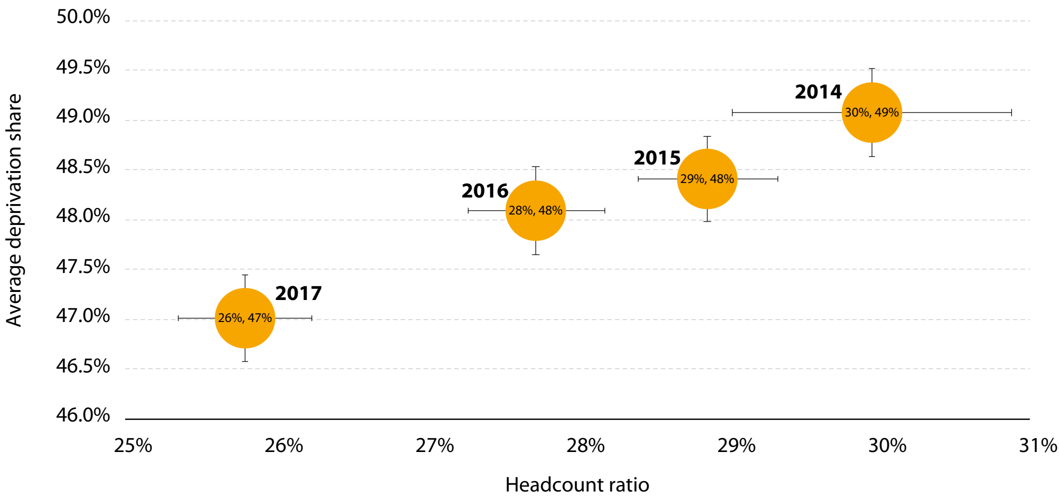
The Europe 2020 social inclusion target is the union of three indicators. Similarly, MPI1 identifies a person as poor if they are deprived in at least one of the three equally weighted indicators (union of AROP, QJ and SMD). In the pooled data set, the cross-sectional MPI1 across the 26 included countries fell from 30 % to 25.8 % between 2014 and 2017 and the percentage of individuals in multidimensional poverty dropped from 30 % to 25.8 %. The intensity of poverty is the average deprivation score of multidimensionally poor people: the deprivation score for someone deprived in one indicator is 1/3 (33 %); in two indicators, 2/3 (66 %); in all three, 3/3 (100 %). It fell from 49.1 % to 47 % during the same period. Figure 16.1 depicts the 95 % confidence intervals of the evolution of MPI1 headcount and intensity between 2014, 2015, 2016 and 2017 and shows that the total changes differ significantly from zero.

Table 16.5 provides a taxonomy of the MPI1 dynamics for the entire population. While overall poverty reduced by 4 p.p. between 2014 and 2017, as shown above, there was significant volatility in the multidimensional poverty status of people. For example, 6.6 % of persons were non-poor in 2014 but poor in 2017, and 8.1 % of persons had the same poverty status in 2014 and 2017 but had at least one episode out of poverty in between. A longitudinal analysis thus showcases the extent to which poverty headcount rates of 30–26 % over a short (4-year) period understate how many experience poverty. Actually, poverty affected 41.5 % of the population during at least 1 year, and 40 % of those people (16.2 % of the total) were always poor (i.e. during these 4 years).

As an aside, when only people aged 16+ are considered, the MPI dropped from 0.144 to 0.117 between 2014 and 2017. The index can be interpreted as the percentage of individuals in multidimensional poverty adjusted by the intensity of the deprivation suffered. Alternatively, it represents the percentage of all possible weighted dimensions in which the multidimensionally poor individuals

Figure 16.1: **Cross-sectional MPI1 (headcount and intensity), 95 % confidence interval, 2014–2017, pooled data set**

(%)



Reading note: Each bubble plots the headcount ratio and intensity (average deprivation score) of poverty in each year. The size of the bubble is the number of poor in each year. The lines show the confidence intervals of the year-specific values. In 2017, almost 26 % of people were poor according to MPI1 and the average deprivation score was just over 47 %.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

are deprived. So an MPI of 0.144 means that poor people experience 14.4 % of the deprivations that could be experienced if everyone were deprived in every dimension. The percentage of people in multidimensional poverty fell from 29.8 % to 25.2 %, and the intensity from 53 % to 49 %. All changes were significant. Regarding the dynamics, 58.3 % of the population was never poor and 15.4 % was always poor. Between 2014 and 2017, 11.3 % of the population moved out of poverty and 6.72 % became poor. These trends are very close to those for the entire population presented in Figure 16.1 and Table 16.5.

The chronic MPI1 takes into account three aspects as explained in Section 16.3.1: the percentage of chronically poor individuals adjusted by the intensity and duration of their condition. To construct the index, we define as chronically poor all persons who were ever multidimensionally poor in that they were deprived in at least one of the three dimensions (k = 1/3) for at least one period (τ = 1) – a condition that affected 41.5 % of the population. This chronic poverty identification includes those who are always poor in all four periods (16.2 %), and also individuals who are poor only in one period (10.1 %), only in two periods (8.2 %) and only in three periods (7.1 %). We then take into account the intensity of deprivation and the duration of poverty of these people. The resulting value (H × A × D, where A is average duration) is presented in Figure 16.2 for each country (for the entire population, i.e. including children), and each component of it is shown in Table 16.6, as well as the MPI1 dynamics by country.

The new feature of this index is duration, which shows the percentage of the four spells in which the average poor person was in poverty. As shown in Table 16.6, on average, poor persons were deprived in two thirds of the 4 years. However, this ranges from a low of 57.7 % in Czechia to a high of 79.3 % in Bulgaria, which means that the average duration of poverty ranged from 2.3 to 3.2 out of 4 years. The total chronic MPI1 ranges from 0.043 (in Sweden) to around 0.23 in Greece and 0.25 in Bulgaria and Romania.

Table 16.5: MPI1 dynamics, three dimensions, 2014–2017
(%)

Poverty dynamics	2014	2015	2016	2017	% (CI)	Aggregated % (CI)
Never poor	Not poor	Not poor	Not poor	Not poor	58.5 (58–59)	58.5 (58–59)
Not poor with changes	Not poor	Not poor	Poor	Not poor	1.9 (1.8–2.1)	5 (4.8–5.2)
	Not poor	Poor	Not poor	Not poor	2 (1.8–2.1)	
	Not poor	Poor	Poor	Not poor	1.1 (1–1.2)	
Moving out of poverty	Poor	Not poor	Not poor	Not poor	3.9 (3.7–4.1)	10.7 (10.4–11.1)
	Poor	Not poor	Poor	Not poor	0.8 (0.7–0.9)	
	Poor	Poor	Not poor	Not poor	3.1 (2.9–3.3)	
	Poor	Poor	Poor	Not poor	3 (2.8–3.2)	
Moving into poverty	Not poor	Not poor	Not poor	Poor	2.3 (2.1–2.4)	6.6 (6.3–6.8)
	Not poor	Not poor	Poor	Poor	1.8 (1.7–2)	
	Not poor	Poor	Not poor	Poor	0.6 (0.5–0.7)	
	Not poor	Poor	Poor	Poor	1.9 (1.7–2)	
Poor with changes	Poor	Not poor	Not poor	Poor	0.8 (0.7–0.9)	3.1 (2.9–3.2)
	Poor	Not poor	Poor	Poor	1.1 (1–1.2)	
	Poor	Poor	Not poor	Poor	1.1 (1–1.2)	
Always poor	Poor	Poor	Poor	Poor	16.2 (15.8–16.5)	16.2 (15.8–16.5)

Note: CI, confidence interval.

Reading note: This table provides an exhaustive set of 16 profiles of how people's poverty status could have changed between 2014 and 2017. While 58.5 % were never poor and 16.2 % were always poor, 25.3 % of the population experienced a combination of poor and non-poor episodes during this period.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

Going beyond the average, we can see that the percentage of the population in a country who are always poor ranges from 4.8 % in Sweden to 41.7 % in Romania – a tremendous gradient.

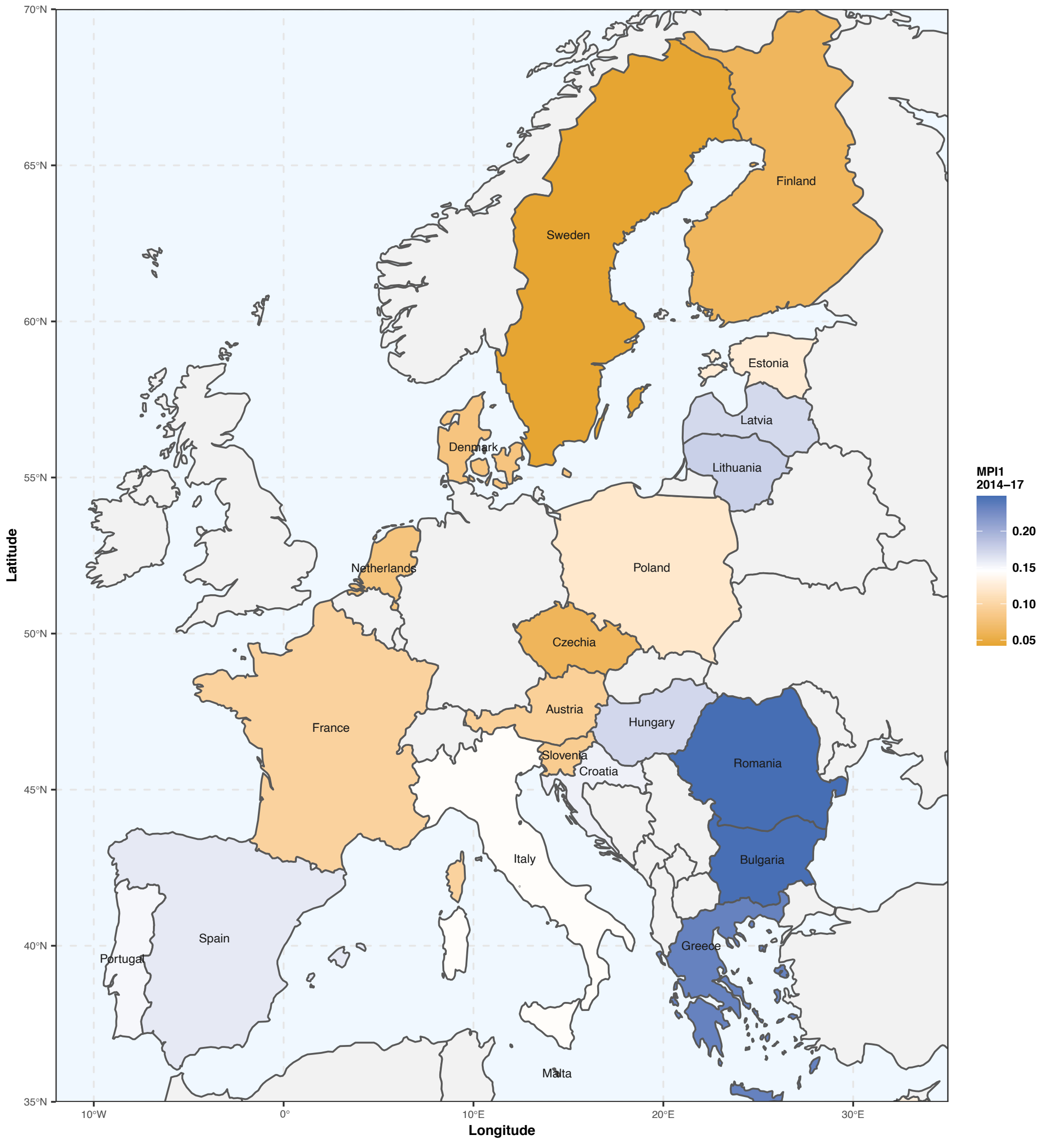
Figure 16.3 orders the countries by the chronic MPI1 (right axis, line). The bars show the percentage of people who are poor, from which it is evident that Romania has both the highest absolute level and the highest proportion of poor people who are always poor. Confidence intervals of 95 % are shown.

Completing the analysis, Figure 16.4 provides the dimensional composition of poverty. This dimensional breakdown is directly available from the MPI, because the combined MPI aggregates the (weighted) headcount ratios in each indicator. Figure 16.4 shows that the gradient across the six poorest countries is driven by the larger contributions of the MSD indicator (Latvia, Hungary, Lithuania, Greece, Bulgaria and Romania), whereas AROP contributes the most in the majority of other countries. QJ varies in its contribution but never contributes the most of the three indicators.

These charts illustrate in a simple way the toolkit available when using chronic multidimensional poverty indexes in an international context, in order to illustrate the diversity of countries in terms of multidimensional poverty rate, duration, intensity and dynamics.

The next section will enlarge the dimensional coverage of the chronic multidimensional poverty index, by including in the analysis the health, housing and education deprivations.

Figure 16.2: **Chronic multidimensional poverty, MPI1, 2014–2017**



Reading note: This figure maps the level of chronic multidimensional poverty.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

Table 16.6: Chronic multidimensional poverty and MPI1 dynamics by country, 2014–2017

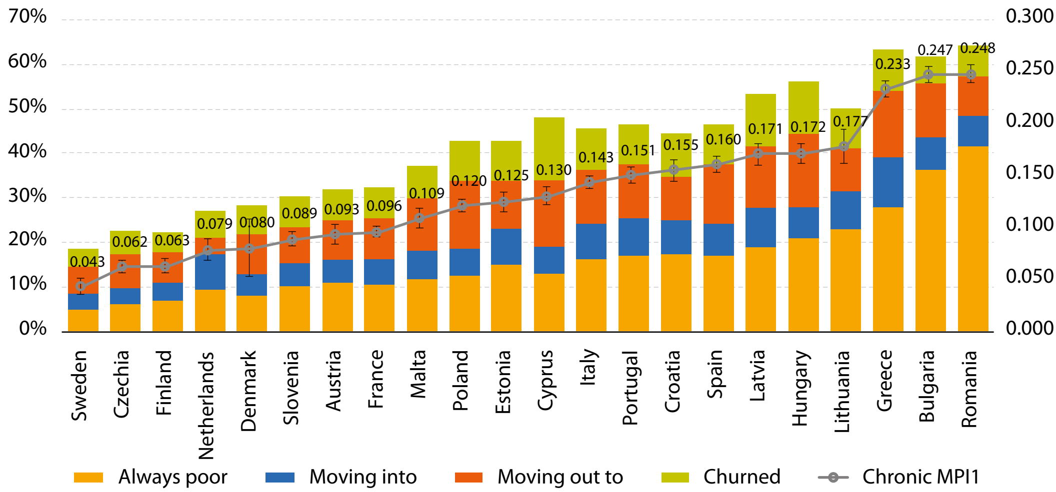
Country	Chronic multidimensional poverty (k = 1/3 and τ = 1)				Dynamics (%)					
	H (%)	A (%)	D (%)	Index	Always poor	Never poor	Moved into	Moved out of	Churned	% of poor who are 'always' poor
Sweden	17.2	59.6	42.2	0.043	4.8	81.3	3.7	5.9	4.3	27.9
Czechia	22.5	57.7	47.9	0.062	6.3	77.5	3.5	7.7	5.0	28.0
Finland	22.1	62.1	45.9	0.063	7.0	77.7	3.8	6.9	4.7	31.7
Netherlands	27.1	63.2	45.8	0.079	9.2	72.8	8.2	3.7	6.2	33.9
Denmark	28.2	59.4	47.9	0.08	7.9	71.8	5.2	8.9	6.3	28
Slovenia	30	63.6	46.5	0.089	10.2	69.7	5.2	7.9	7.1	34
Austria	32	64	45.3	0.093	10.9	68	5.2	9	7	34.1
France	30.9	63.9	48.4	0.096	10.3	67.8	5.7	9.2	7	33.3
Malta	37.1	62.3	47	0.109	11.7	62.9	6.4	11.5	7.5	31.5
Poland	42.4	62.7	45.3	0.12	12.6	57.2	5.9	15.4	9	29.7
Estonia	42.2	64.9	45.7	0.125	15.1	57.3	8.1	10.6	9	35.8
Cyprus	48	61	44.5	0.13	12.9	52	6	15.2	14	26.9
Italy	45.6	66.2	47.4	0.143	16.2	54.4	7.9	12.3	9.2	35.5
Portugal	45.9	66.9	49	0.151	16.8	53.7	8.7	12	8.9	36.6
Croatia	44	68.3	51.6	0.155	17.5	55.7	7.5	9.8	9.6	39.8
Spain	45.7	67.7	51.8	0.16	16.7	53.7	7.6	13	9	36.5
Latvia	52.8	66.5	48.7	0.171	19	46.9	8.8	13.9	11.4	36
Hungary	55.7	66.1	46.6	0.172	21	44.1	6.9	16.4	11.6	37.7
Lithuania	49.7	70.8	50.4	0.177	22.8	50	8.6	9.9	8.7	45.9
Greece	63.2	72	51.3	0.233	27.9	36.7	11.1	15	9.3	44.1
Bulgaria	61.8	79.3	50.4	0.247	36.4	38.1	7.4	11.9	6.2	58.9
Romania	64.2	82.2	46.9	0.248	41.7	35.8	6.7	9	6.9	65
All	41.50	67.7	48.3	0.135	16.2	58.5	6.6	10.7	8.1	39.2

Note: A, average duration; D, average deprivation score; H, headcount ratio.

Reading note: This table provides the chronic poverty H, A and D, plus a set of five profiles of how people's poverty status could have changed from 2014 to 2017. The combined categories are introduced in Table 16.5. Countries are ranked according to the value of the chronic multidimensional poverty index.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

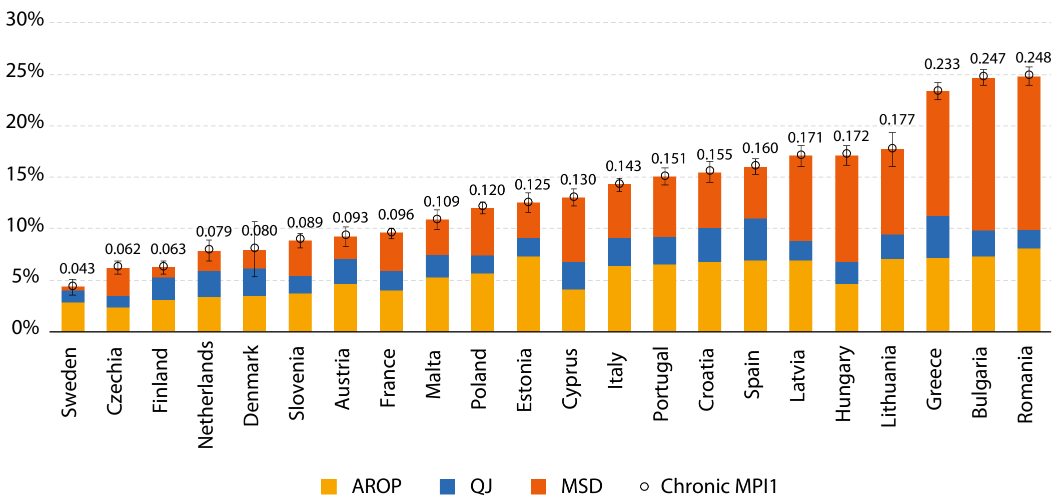
Figure 16.3: Chronic multidimensional poverty (MPI1) index (right-hand axis) and dynamics in longitudinal poverty, 2014–2017
(%, left-hand axis)



Reading note: The bar chart provides the headcount ratio of ever-poor persons (right-hand axis). The bar sections show the subsets of the poor who were always poor, or who moved into or moved out of poverty during 2014–17 (left-hand axis). The line shows the level of the chronic multidimensional poverty index (right-hand axis).

Source: Authors' computations, UDB 2019-1, weighted by RB064.

Figure 16.4: Contribution by indicator to chronic multidimensional poverty (MPI1), 2014–2017
(%)



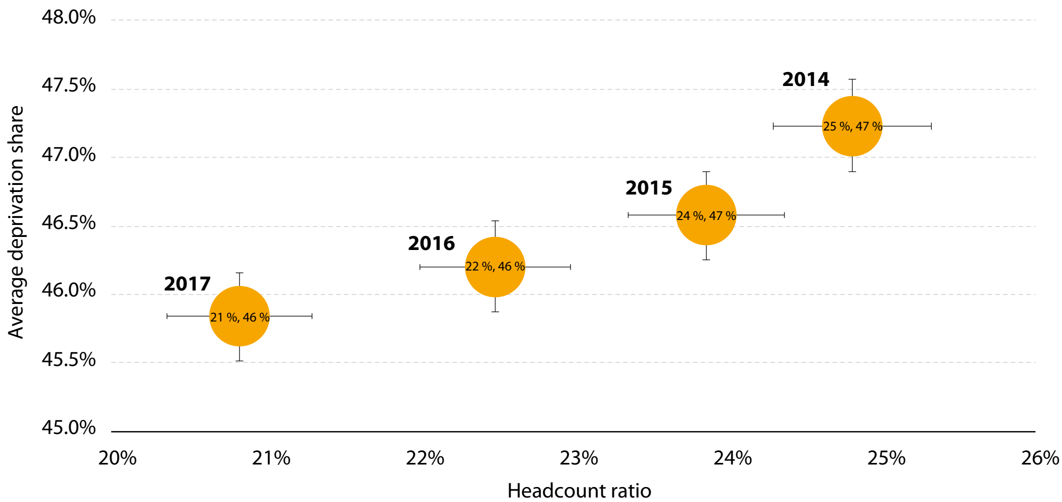
Reading note: Because the chronic MPI can be consistently broken down into its dimensional components, this shows the contribution of deprivations in each indicator to overall chronic MPI1. We see that MSD contributes the most in Romania.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

16.5. Dynamics of the extended multidimensional poverty indicator, adult population

We turn now to the extended multidimensional poverty indicator (MPI2), the 6-dimension, 10-indicator measure computed for the adult population only. Cross-sectionally, Figure 16.5 shows a similar pattern to Figure 16.1, in that 24.8 % of the pooled sample of adults (aged 16+) were multidimensionally poor in 2014, reducing to 20.8 % in 2017. The reduction from 2014 to 2017 was statistically significant each year. Intensity likewise decreased. Using a poverty cut-off of 1/3, which now means that a person must be deprived in at least two of the six dimensions to be identified as multidimensionally poor, we find that 65.6 % of people were never poor and 34.4 % were poor in at least one period (see Table 16.7). The dynamics of poverty are also similar to the three-dimensional case (Table 16.5), with 12.9 % of people being always poor. This percentage is just over half of the multidimensionally poor in 2014 (25 %) and under one third of the ever-poor (34.4 %). So, despite having different dimensional and indicator configurations, both measures tell similar stories regarding the dynamics and volatility of multidimensional poverty.

Figure 16.5: Cross-sectional MPI2 (headcount and intensity), 95 % confidence interval, 2014–2017, pooled data set
(%)



Reading note: This figure plots the headcount ratio and intensity (average deprivation score) with their 95 % confidence intervals for each year 2014–2017.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

Table 16.7: MPI2 dynamics, $k = 1/3$, 2014–2017
(%)

Poverty dynamics	2014	2015	2016	2018	% (CI)	Aggregated % (CI)
Never poor	Not poor	Not poor	Not poor	Not poor	65.6 (65.6–65.6)	65.6 (65.6–65.6)
Not poor with changes	Not poor	Not poor	Poor	Not poor	1.6 (1.6–1.6)	4.4 (4.4–4.5)
	Not poor	Poor	Not poor	Not poor	1.9 (1.9–1.9)	
	Not poor	Poor	Poor	Not poor	1 (0.9–1)	
Moving out of poverty	Poor	Not poor	Not poor	Not poor	3.2 (3.2–3.2)	9.1 (9.1–9.1)
	Poor	Not poor	Poor	Not poor	0.8 (0.8–0.8)	
	Poor	Poor	Not poor	Not poor	2.6 (2.6–2.6)	
	Poor	Poor	Poor	Not poor	2.5 (2.5–2.5)	
Moving into poverty	Not poor	Not poor	Not poor	Poor	1.9 (1.9–1.9)	5.2 (5.1–5.2)
	Not poor	Not poor	Poor	Poor	1.3 (1.3–1.3)	
	Not poor	Poor	Not poor	Poor	0.5 (0.5–0.5)	
	Not poor	Poor	Poor	Poor	1.5 (1.5–1.5)	
Poor with changes	Poor	Not poor	Not poor	Poor	0.7 (0.7–0.7)	2.8 (2.8–2.8)
	Poor	Not poor	Poor	Poor	1 (1–1)	
	Poor	Poor	Not poor	Poor	1.1 (1.1–1.1)	
Always poor	Poor	Poor	Poor	Poor	12.9 (12.8–12.9)	12.9 (12.8–12.9)

Note: CI, confidence interval.

Reading note: This table provides an exhaustive set of 16 profiles of how people's poverty status could have changed between 2014 and 2017. While 65.6 % were never poor and 12.9 % were always poor, 21.5 % of the population experienced a combination of poor and non-poor episodes during this period.

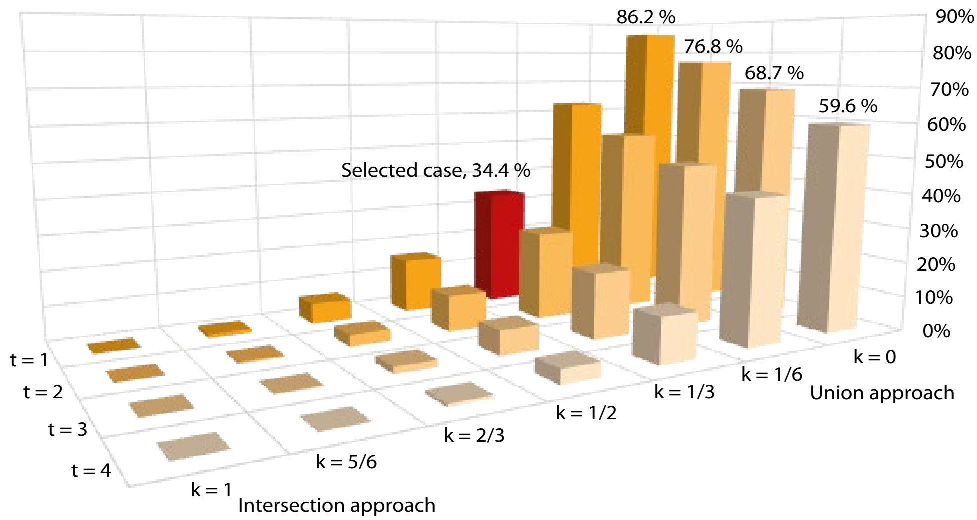
Source: Authors' computations, UDB 2019-1, weighted by RB064.

Figure 16.6 visually depicts the sensitivity of the headcount ratios for multidimensional poverty with all possible cross-dimensional k and duration τ cut-offs. Fully 86.2 % of the population were deprived in at least one indicator during one period and 59.6 % in all four periods, while the proportion of those deprived in five or more of the dimensions for any duration is small. Around one third of the adult population (34.4 %, our selected case) were deprived in at least one period in at least one third of the weighted indicators (so two to four indicators at a minimum, depending on weights) and 12.9 % in all 4 years. Intertemporally, we observe that the case of $k = 1/6$ has a similar 'chronicity' gradient to union in terms of the difference between the always poor and those deprived in only one period (about 20 p.p.), and that the gradient is the largest in absolute terms for the case of $k = 1/3$.

Hence, an analysis of multidimensional chronic poverty – by both intensity and duration – adds value to the analysis using a purely cross-sectional approach, and the choice of threshold influences the chronicity gradient.

Table 16.8 provides the country-wise estimations for $k = 1/3$ and a duration cut-off of 1 ($\tau = 1$). The average duration of poverty across the pooled data set is roughly two thirds of the period – the same as the three-dimensional measure (see Table 16.6) – with the highest average duration being 81.9 %, in Romania, and the lowest being 56 %, in Denmark. The percentage of the population who were in multidimensional poverty continuously was 28.8 % in Romania and 23.6 % in Bulgaria, falling to a low of 3.1 % in Sweden. Actually, the patterns of poverty dynamics were rather heterogeneous. In Cyprus and Netherlands, 24–27 % of the poor were always poor in all periods, although in three countries (Romania, Bulgaria and Lithuania) this proportion was 54–66 %. In seven countries (Poland, Slovenia, Greece, Portugal, Hungary, Estonia and Croatia) it was 39–43 %.

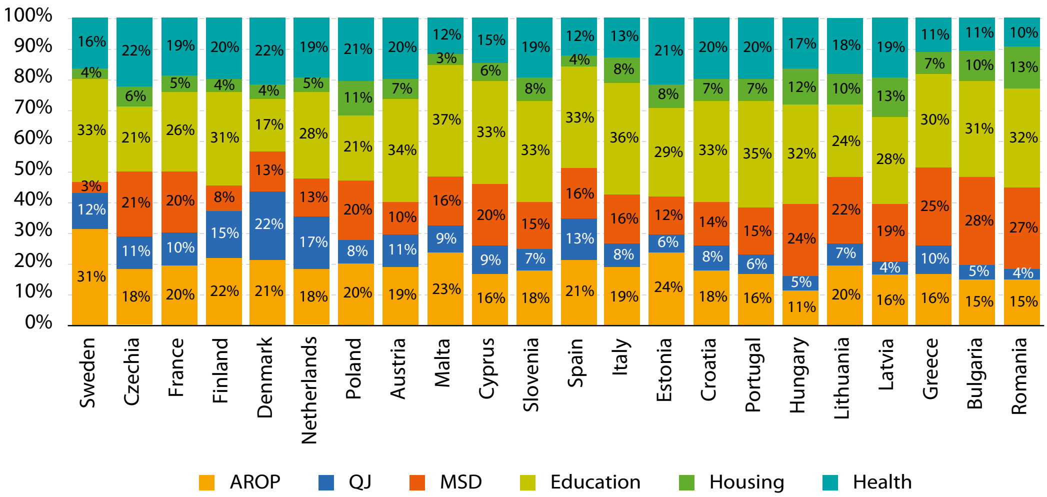
Figure 16.6: Chronic headcount ratios: key duration and poverty cut-offs, 2014–2017
(%)



Reading note: This figure plots the headcount ratio of chronic multidimensional poverty for all possible duration cut-offs and seven possible poverty cut-offs. In the back row and the darkest shade are headcount ratios of persons ever deprived; in the front row and the lightest shade are the headcount ratios of persons who were always deprived in all four periods. On the right-hand side is the union poverty cut-off whereby any person with any deprivation is identified as poor, followed by six rows from 1/6 to 6/6. Thus the leftmost column depicts only those deprived in all indicators. The red bar shows the illustrative selected measure described in subsequent tables.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

Figure 16.7: Composition of chronic MPI2 by indicator, by country, 2014–2017
(%)



Reading note: This shows the contribution of deprivations in each indicator to overall chronic MPI2. For example, in Romania, education deprivation and MSD contribute the most to chronic MPI2.

Source: Authors' computation, UDB 2019-1, weighted by RB064.

Table 16.8: Chronic multidimensional poverty and MPI2 dynamics by country, by country, 2014–2017

Country	Chronic multidimensional poverty (k = 1/3; τ = 1)				Dynamics (%)					
	H (%)	A (%)	D (%)	Index	Always poor	Never poor	Moved into	Moved out of	Churned	% of poor who are 'always' poor
Sweden	9.0	58.2	42.7	0.022	3.1	91.0	1.7	2.4	1.8	34.4
Czechia	16.2	62.8	46.8	0.048	5.8	83.8	3.4	4.7	2.3	35.7
Finland	20.5	62.2	44.4	0.057	6.5	79.5	3.8	6.2	3.9	31.6
Austria	21.1	62.4	44.9	0.059	6.9	78.9	3.8	5.6	4.9	32.6
Netherlands	24.1	57.5	45.0	0.062	5.7	75.9	5.7	3.8	8.9	23.8
France	22.3	62.4	45.1	0.063	7.1	77.7	4.1	5.6	5.5	31.9
Denmark	29.3	56.0	48.0	0.079	8.9	70.7	7.7	5.7	7.1	30.4
Slovenia	26.4	67.0	48.4	0.086	10.5	73.6	4.8	5.5	5.6	39.6
Poland	28.4	67.6	46.1	0.088	11.0	71.7	3.8	8.4	5.2	38.8
Cyprus	33.1	61.4	44.1	0.090	9.0	66.9	4.5	9.6	10.1	27.1
Malta	32.5	63.4	44.2	0.091	10.1	67.5	6.1	8.9	7.4	31.0
Estonia	35.3	68.9	47.0	0.114	14.6	64.7	7.3	7.0	6.5	41.2
Italy	41.9	62.6	45.1	0.118	12.1	58.1	5.2	14.0	10.6	28.9
Hungary	37.3	67.1	48.7	0.122	15.3	62.7	3.8	9.9	8.3	41.1
Spain	41.1	66.9	46.4	0.127	14.1	58.9	6.7	11.6	8.8	34.3
Croatia	38.1	70.6	48.8	0.131	16.3	61.9	6.9	7.0	7.9	42.8
Latvia	41.9	66.8	49.1	0.137	16.1	58.1	7.2	9.6	9.1	38.4
Lithuania	39.5	75.6	50.6	0.151	21.3	60.5	6.8	6.2	5.2	53.9
Bulgaria	42.2	76.7	50.8	0.164	23.6	57.9	6.1	7.2	5.3	55.9
Greece	51.4	69.6	45.8	0.164	20.4	48.6	9.1	12.6	9.3	39.7
Portugal	51.1	69.6	47.0	0.167	20.8	48.9	7.9	12.3	10.2	40.6
Romania	43.9	81.9	49.2	0.177	28.8	56.1	4.5	6.9	3.7	65.6
Total	34.4	66.9	46.5	0.107	12.9	65.6	5.2	9.1	7.2	37.5

Note: A, average duration; D, average deprivation score; H, headcount ratio.

Reading note: This table provides the chronic poverty H, A and D, plus a set of five profiles of how people's poverty status could have changed from 2014 to 2017. The combined categories are introduced in Table 16.5. Countries are ranked according to the value of the chronic multidimensional poverty index.

Source: Authors' computations, UDB 2019-1, weighted by RB064.

Figure 16.7 provides the percentage contribution of each indicator to the chronic MPI2 (k = 1/3; τ = 1). The countries are ranked from poorest to least poor by the chronic MPI2. We see that the indicator composition varies among the three indicators used in MPI1 (AROP, MSD, QJ), which are depicted at the bottom of the graphic. AROP and QJ tend to contribute the least in the poorest countries, where it is MSD that contributes the most, as for MPI1. Education deprivation, third from the top, contributes the most to chronic MPI in every country except in Czechia. This may be because education deprivation is highly correlated with the other problems (AROP, MSD and QJ). The housing indicator contributes most in eastern countries (see also Chapter 12 of the present volume). There appear to be considerable divergences across countries in the health/housing/education indicator patterns, which suggests that there could be value in adding these dimensions in a chronic EU MPI if the information is comparable and policy sensitive.

16.6. Conclusion

The longitudinal information in EU-SILC exploited in this chapter greatly expands our information horizon, showing that, among people who were multidimensionally poor at least once during the 4 years covered, around 40 % were poor in all four periods. This chapter also illustrates how the duration of deprivations differs by indicator, and also by country. Using the longitudinal information in this way greatly expands the policy relevance of the MPI to understand poverty dynamics, especially in terms of (1) persistence (between 2014 and 2017, 16.2 % and 12.9 % of the population remained in poverty according to MPI1 and MPI2 respectively); (2) transitions over time (depending on the measure, between 9.1 % and 10.7 % of the population moved out of poverty in the period); (3) heterogeneity across groups (the difference between the best and the worst performer in terms of chronic multidimensional poverty is 5.8 times in MPI1 and 8 times in MPI2).

The charts and tables provided in this chapter illustrate in a simple way the information platform that is available when using chronic multidimensional poverty indexes. The choice of dimensions and cut-offs remains to be made at EU level, but the information platform can easily provide, for each Member State, the multidimensional poverty rate, duration, intensity and dynamics.

At the same time, many outstanding research issues could not be addressed for lack of space but can easily be. For example, where data permit, it would be highly desirable to disaggregate this analysis by gender, as well as other demographic and social groups such as employment category, household size or type, rural–urban location and age cohort. The composition of poverty by indicator varies considerably and it would be useful to assess different regional groupings of countries to identify commonalities and differences. Naturally, the most important extension would be to ascertain how fast-moving countries reduced MPI within that 4-year period. This exercise is thus a first step and we hope it will give rise to several additional longitudinal studies.

The other significant challenge is data constraints. Our earlier paper (Alkire and Apablaza, 2017) noted the comparability difficulties across countries in the level of education indicator and suggested replacing this with years of schooling plus lifelong learning qualifications, but such comparable flow data remain unavailable. As we observed previously, the available data do not allow between-country comparisons of the years of schooling because only the level of schooling is recorded, but this is equivalent to different years of schooling in different countries. Data on lifelong learning are able to capture improvements in lifelong learning that counteract education deprivations during school-aged years – be it for citizens or for migrants. Furthermore, the redundancy of the 'current' education indicator is higher than other indicators. This creates a dilemma: low human capital reflects a direct deprivation and has instrumental importance in perpetuating poverty. It is therefore a policy decision whether a future MPI for the EU would include education as a placeholder, until comparable flow data are available, or exclude it.

The housing indicators are unexpectedly not redundant alongside MSD, although overcrowding has a higher overlap. Furthermore, the dwelling deprivation headcount ratios are high and more volatile than expected, so they seem to add value to the analysis.

Similarly, the health indicators do not overlap with the other indicators and clearly bring into view an important dimension of poverty and social exclusion, which is crucial in the (post-)pandemic period. It is true that the health data, being self-reported, are not necessarily accurate proxies for the objective health condition of the person and can reflect different health problems, but some studies assess that they are sufficiently strong proxies for these purposes. Therefore, in our view it would be desirable to use the six-dimension indicator, albeit with improved educational information.

The exercises presented here – of both building an MPI longitudinally and extending it to include health, housing and education – are highly relevant for the post-2020 strategy during the pandemic period. Given the SDGs' focus on interconnections across indicators – because such an understanding can inform efficient multisectoral policies – and given also the evident value of longitudinal analysis, we hope that this study sparks additional analyses of the differing ways that multiple deprivations overlap and combine over time so that they can be effectively addressed to end poverty in all its forms and dimensions.

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Methodological and conceptual issues linked to the design and coverage of EU-SILC

17 Rotation group bias in European Union social indicators

Alessio Fusco, Giovanni Gallo and Philippe Van Kerm (176)

17.1. Introduction

Rotating panel design represents an efficient strategy to improve the precision of estimates of change in population parameters. It also offers (to some extent) the advantages of 'pure' panels (i.e. following specific individuals over time to allow longitudinal inference) while mitigating some of their pitfalls, such as attrition, which affects the sample representativeness of the population. A natural question arising from the use of rotating panel design is to what extent it may influence estimates of cross-section quantities, compared with traditional cross-section designs. In rotating panel designs, each new sample is typically drawn using the same design on each occasion and is meant to be representative of the target population at the time of sampling. The validity of the approach is based on the idea that, at any point in time, each 'rotation group' remains representative of the target population, irrespective of its vintage. Systematic discrepancies observed in estimates across rotation groups are referred to as 'rotation group bias' (Krueger et al., 2017).

In the context of employment statistics, Krueger et al. (2017) document a rotation group bias in the estimation of unemployment rates through the US Current Population Survey. Although the sample of each rotation group is supposed to be representative of the same target population, estimated unemployment rates tend to be lower in older rotation groups – that is, for samples that have already been interviewed on several occasions – than for the newer ones, which have been recently incorporated in the survey. The magnitude and shape of this bias grew significantly from 1976 to 2014.

EU-SILC relies on a rotating panel sample, in which the design recommended by Eurostat consists of including four rotating groups per wave (Eurostat, 2015, 2019). Any rotation group sampled from the target population remains in the survey for 4 years, and every year one group is dropped and replaced by a new sample. While a small literature has studied the effect of rotational group design on employment statistics (e.g., Krueger et al., 2017), little is known about this effect on social indicators. The aim of the present chapter is to examine to what extent the rotational design of EU-SILC affects the estimates of a selected subset of EU social indicators (see Section 17.2.2). We ask if there is a rotation group bias, that is, as Krueger et al. (2017, p. 258) define it, 'a systematic tendency for differences in estimates across rotation groups', when applied to each of these indicators.

Rotation group bias can arise for at least three reasons. The first is differential panel attrition. The characteristics of survey participants who drop out from the survey may differ from the characteristics of retained survey participants. This may therefore change the composition of the rotation groups over time in non-random ways. People who drop out are more likely to be female, young, foreign

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born, less educated, in poor health, on a low income, full-time employed and residentially mobile (Michaud et al., 2011). Second, rotation group bias can arise from changes in reporting behaviour across repeated interviews, a phenomenon called panel conditioning or time-in-survey effect. Being repeatedly subjected to the same questions over a relatively short time may activate a potential learning process (Fisher, 2019). Therefore, responses by older rotation groups may vary from those of the newer groups, given their repeated participation in the survey. Third, estimates based on different rotating samples may arise from changes in the underlying target population. Rotating samples are drawn at different points from a target population whose composition may change over time. Along with deaths and births, in- and outmigration flows continuously modify the population present in the sampling frame. For example, among most EU countries, immigration flows relative to the total population were (in 2018) between 0.4 % (in Portugal) and 1.4 % (in Spain and Slovenia); see Eurostat (2020) ([177]). This may lead to non-random differences in rotation group sample composition if the new population members differ systematically from the original population ([178]).

The rotation group bias question is closely related to the analysis of the coherence between cross-sectional and longitudinal samples in EU-SILC. Longitudinal samples are composed of all rotation groups except the newly added one (and one can further restrict them to households present for three or four waves). Comparison of estimates of cross-sectional statistics obtained from the cross-section and the longitudinal samples is therefore a way to examine sensitivity to rotational design. Glaser et al. (2015) find a 2 p.p. discrepancy in the AROP estimates based on 2-, 3- or 4-year longitudinal panels and the cross-sectional one in the 2007 Austrian EU-SILC samples. The discrepancy disappears from 2008 onwards, a finding that they attribute to a change in both the fieldwork (i.e. change in interviewers and interview technique) and the controls used for calibration. Extending their analysis beyond Austria, Glaser et al. (2015) also find discrepancies between estimates based on a 2-year panel and the cross-sectional sample in Denmark, France, the Netherlands, Finland and Sweden. They explore sources of the rotational group bias – mainly related to sample design characteristics – to explain differences across countries. Although no clear pattern emerges, most incoherence is found in countries relying on register data with a selected respondent design – drawing a sample of adult respondents rather than a sample of households. Glaser et al. (2015) recommend reducing the bias by adjusting sample weights through a longitudinal calibration procedure. Krell et al. (2017) provide another thorough analysis of the coherence between cross-sectional and longitudinal income information. Using EU-SILC 2005–2009 data, they find substantial deviations in estimates of some inequality and poverty indicators between cross-sectional and 2-year longitudinal samples. As in Glaser et al. (2015), these deviations are particularly large in countries deriving income information from register data such as Denmark, Norway and Sweden, but also in Bulgaria, Czechia, Germany and France. Similar comparisons of estimates derived from cross-sectional samples and longitudinal samples are provided by Jenkins and Van Kerm (2017) for AROP indicators. Again, deviations are observed in a range of countries, but no clear pattern emerges in relationships to other sample design characteristics.

The present chapter extends this work by (1) examining a broader set of EU indicators; (2) comparing all rotation groups (the coherence between longitudinal and cross-sectional samples effectively emphasises differences only between the new rotation group and the rest); and (3) using influence function (IF) regression methods to test the existence of a rotation group bias and to assess whether the rotation group bias is linked to systematic differences in sample composition or to differences in responses conditional on sample composition.

([177]) Exceptions are Malta (5.5 %), Luxembourg (4 %), Cyprus (2.6 %), Ireland (2 %) and Slovakia (0.1 %).

([178]) Probabilities of sampling new immigrants and their responding may, however, be low, and therefore mitigate this source of rotation group bias: sampling frames are not necessarily adjusted sufficiently frequently to include them (e.g. when sampling is from population censuses) and their response rates tend to be low. In practice, with the exception of Luxembourg, fewer than 3 % of the EU-SILC cross-section respondents immigrated into their country of residence less than 6 years before. The share is less than 1 % in more than half of the countries. See Chapter 5 on the coverage of immigrants in EU-SILC.

This chapter is organised as follows. Section 17.2 presents the data and the set of EU indicators analysed, while Section 17.3 briefly describes the methodology. Section 17.4 shows estimation results based on different model specifications. Section 17.5 concludes.

17.2. Data and social indicators

17.2.1. Data

EU-SILC builds on a rotating panel sample, in which the recommended design by Eurostat consists in selecting four panels per wave. Every year, one fresh sample is sampled from the target population, and the sample members are interviewed over 4 years. A few countries implemented different designs over time. For instance, in the 2014 EU-SILC, the French component relies on a 9-year rotating panel design, and Norway's on an 8-year rotating panel design, while the United Kingdom's cross-sectional data are a 'pure' cross-sectional sample entirely renewed every year ([179]). Norway moved to a 4-year rotating panel design after 2014.

Our analysis draws on 2014 EU-SILC cross-section data and covers all countries included – a total of 29 – except Norway, Serbia (which started less than 4 years before the 2014 survey) and the United Kingdom. We examine France despite the difference in design. After excluding cases with missing values for important covariates, zero individual weight and non-positive incomes, the analysis is carried out on a data set of 550 909 individuals.

Table 17.1 shows the sample size by country and rotation group ordered by maturity (i.e. 1, first year in the sample; 2, 2 years in the sample; and so on). In the majority of countries, the number of observations declines with the maturity of the group (older samples have smaller observations) but the decrease in sample size varies across countries. This is to be expected, since older rotation groups are exposed to cumulative attrition over time. There are, however, a few exceptions, as the size of the samples depends not only on attrition but also on the initial number of respondents, which may vary across rotation groups and can cause upward or downward differences in rotation groups' sample sizes.

It is important to note that the identification of the maturity of the rotation groups is not directly available and is our own construction here. EU-SILC variable DB075 identifies the rotation group of each observation in the cross-sectional UDB. There is, however, no direct identification of the year of entry into the sample – for example, coding a rotation group as 1 does not identify when the group entered the sample – because not all countries joined EU-SILC at the same time or have used the same number of rotation groups since the beginning of the survey (Eurostat, 2016). To reconstruct the entry year of each rotation group and country in 2014, we looked at sample population changes by group across time using the cross-sectional data from 2010 to 2014, and consulted national quality reports. Once the newest rotation group of the four is identified, most countries follow the standard numbering (e.g. if the newest group in 2014 is numbered 4, then number 3 was the newest in 2013, and so on), with a few exceptions (Ireland, Croatia and Malta).

([179]) A different rotating panel design is used for the United Kingdom's EU-SILC longitudinal sample, but these observations do not enter the cross-sectional sample. Luxembourg is another peculiar case, as the Luxembourgish component of EU-SILC followed a pure panel sample until 2012 and adopted, from 2013 onwards, the standard 4-year rotating panel design.

Table 17.1: Sample observations by country and rotation group (ordered by maturity)

Country	Rotation group				
	1	2	3	4	Pooled
Belgium	4 318	3 913	3 164	2 889	14 284
Bulgaria	3 541	2 824	2 817	2 976	12 158
Czechia	5 009	4 333	4 024	4 839	18 205
Denmark	5 074	3 818	3 111	1 829	13 832
Germany	8 336	6 729	5 494	5 617	26 176
Estonia	4 277	3 785	3 715	3 168	14 945
Ireland	7 688	3 390	1 611	1 013	13 702
Greece	7 698	7 112	3 355	2 800	20 965
Spain	9 360	8 107	7 549	6 357	31 373
France	4 503	3 731	4 031	14 296	26 561
Croatia	4 819	3 216	3 135	2 809	13 979
Italy	14 516	11 154	11 005	10 033	46 708
Cyprus	3 261	2 516	3 559	2 689	12 025
Latvia	3 817	3 315	3 321	3 254	13 707
Lithuania	3 651	2 653	2 877	2 679	11 860
Luxembourg	3 269	2 569	2 252	1 790	9 880
Hungary	5 487	5 154	4 263	7 728	22 632
Malta	3 181	3 075	2 708	2 838	11 802
Netherlands	7 768	6 124	5 202	5 153	24 247
Austria	4 240	3 177	2 866	2 691	12 974
Poland	10 076	9 019	9 039	7 795	35 929
Portugal	4 687	4 448	4 155	3 931	17 221
Romania	4 321	4 384	4 194	4 335	17 234
Slovenia	9 290	7 007	6 247	5 153	27 697
Slovakia	4 413	3 966	3 692	3 617	15 688
Finland	7 780	6 851	6 119	6 135	26 885
Sweden	3 733	3 455	3 116	3 512	13 816
Iceland	2 362	2 289	2 028	2 117	8 796
Switzerland	4 493	3 814	3 576	3 745	15 628
Total	164 968	135 928	122 225	127 788	550 909

Note: Observations in ordered rotation group 1 were interviewed for the first time in 2014, those in rotation group 2 in 2013, those in rotation group 3 in 2012 and those in rotation group 4 in 2011. For France, rotation groups 5–9 are combined in rotation group 4.

Reading note: In 2014, there were 4 318 observations in the first rotation group in Belgium. The full sample is composed of 14 284 observations.

Source: Authors' computations, UDB March 2017.

17.2.2. Four social indicators

We examine four EU commonly agreed social indicators (Social Protection Committee, 2015; Atkinson et al., 2017). Following EU conventions, we adopt as our income definition the total household equivalised disposable income (see Chapter 2 for more details). The same income value is assigned to each member of the household, but the analysis is run at individual level applying individual cross-section sample weights to all estimates.

For income inequality, we look at the Gini index. For poverty and social exclusion measurement we use the Europe 2020 strategy's AROPE rate (see Chapter 1 of the present volume for the definitions of its three components). We also analyse each component separately. Instead of analysing the SMD rate included in the AROPE indicator, we analyse the newly agreed MSD rate (see Guio et al., 2017; Chapter 1 above). Previous research described above mainly focused on AROP but, as we show, rotation group bias is observed in other indicators, including those not based (exclusively) on income.

17.3. Assessing rotation group bias

The first and simplest strategy to assess the size of a rotation group bias is to estimate the indicators in each of the four rotation groups separately – $\theta^{(1)}$, $\theta^{(2)}$, $\theta^{(3)}$ and $\theta^{(4)}$ – and to try to detect any statistically significant variations across estimates. In the absence of rotation group bias, we expect no statistically significant differences across subgroup estimates. For example, we can test the null hypothesis that $\theta^{(1)} = \theta^{(2)} = \theta^{(3)} = \theta^{(4)}$ against the alternative hypothesis that $\theta^{(r)} \neq \theta^{(s)}$ for at least one pair r, s. The drawback of this strategy is that subsample estimates $\theta^{(k)}$ are based on smaller numbers of observations than pooled estimates and may be relatively imprecisely estimated. This may limit the possibility of detecting significant variations across subsamples.

An alternative consists in estimating the indicator of interest in the (pooled) cross-sectional sample – as is done to calculate official statistics – and to examine the contribution of sample observations drawn from each of the rotation groups to the estimation of the overall indicator θ. The definition of the contribution of an observation to an aggregate indicator θ is based on the concept of the IF. In a nutshell, the IF captures how much a given social indicator θ responds to an infinitesimal increase in the probability of observing a particular value y in the population. To any functional θ corresponds a different IF (see, for example, Osier, 2009; Verma and Betti, 2011; Graf and Tillé, 2014). Therefore, our second strategy to determine the existence and magnitude of a rotation group bias consists in examining the value of the IF for observations of different rotation groups. In the absence of any rotation group bias, the average IF should be the same in all rotation groups. It can then be demonstrated that, in the absence of rotation group bias, swapping a small number of observations from one rotation group to the other (leaving all else constant, namely the share of the other groups and the distribution of income within each group) should not significantly affect θ. We refer to this impact as the unconditional effect (UE) of rotation groups (for details on the methodology, see Choe and Van Kerm, 2018; Firpo et al., 2009; see Chapter 5 of this volume for an application in another context).

In addition, the IF approach can be used in a regression in order to partial out the effect of potential confounding variables (in our case, age, gender, nationality of the household head, the household size and structure, the employment statuses of household members and the tenure status for their residence) that are potentially correlated with both the IF value and the group membership. This allows us to assess if rotation group membership remains associated with the IF of social indicators after adjusting for differences in these characteristics across groups. We refer to this impact as the conditional effect (CE) of rotational groups. As we expect that control variables are correlated with the key outcome variables (income or deprivation indicators), observing a statistically significant CE signals that the source of rotation group bias is not (only) due to the composition of the rotation groups but is also due to differences in the outcome variables unexplained by the control variables.

We apply cross-section sampling weights in all calculations. EU-SILC sampling weights are adjusted for different potential sources of population unrepresentativeness (i.e. sampling design, non-response and attrition) and calibrated to known population totals (Eurostat, 2015, 2016). Differences in observable household characteristics across rotation groups driven by attrition should be corrected by the application of household weights in calculating the social indicators ([180]). In principle, we should therefore not expect to find many differences between our UEs and CEs of the rotation group bias.

17.4. Results

17.4.1. Differences across rotation groups

Figure 17.1 shows our estimates of social indicators based on the pooled cross-section sample and on separate rotation groups. Several striking differences across rotation groups emerge but no clear pattern can be identified. In many countries, the newest rotation group (group 1) reports a higher level of income inequality and poverty than the three older ones. This is the case for 11 countries (out of 29) for the Gini index, 14 countries for the AROP rate and 12 countries for the AROPE rate. In some countries, the AROP or AROPE rates for people who have been in the sample for 3 or more years are remarkably lower than those reported by rotation group 1 (e.g. in Czechia, Denmark, Germany, France, Cyprus and Slovakia).

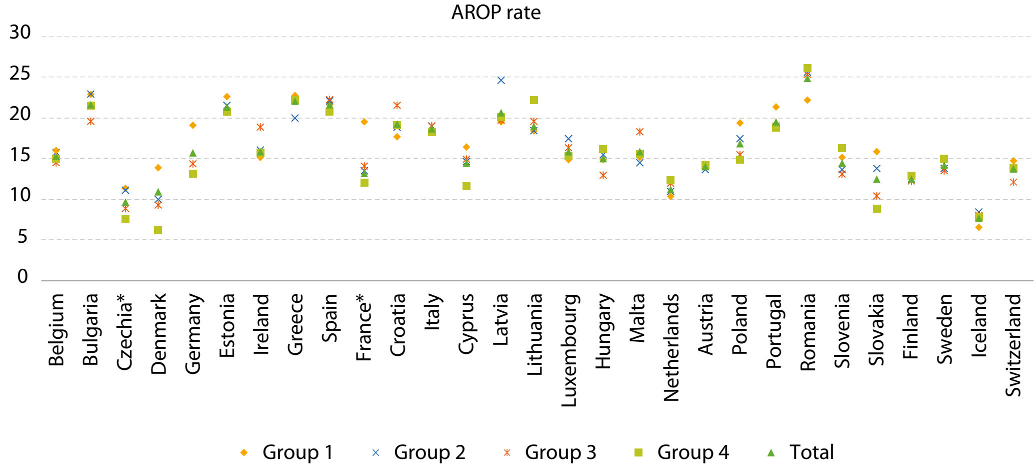
However, many of those differences are not statistically significant. Equality of rotation group estimates of AROP is rejected in only two countries (Czechia and France) ([181]). For the Gini coefficient, equality is rejected in five countries (Czechia, Denmark, Germany, Austria, Slovakia). This reassuring picture, however, grows more problematic when SMD and QJ indicators are introduced: equality of estimates across rotation groups is rejected in seven countries for AROPE and in nine countries – almost a third – for the SMD rate. Taken together, out of 29 countries examined, 12 show signs of rotation group bias in at least one of the four indicators.

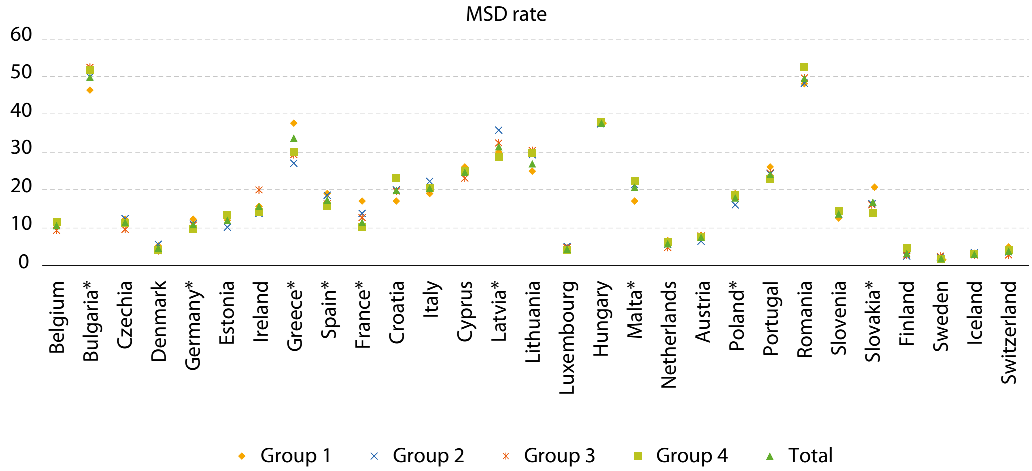
One problem with this testing approach is that the indicators examined have potentially relatively large sampling variability (because they are sensitive to the tails of the income distribution or depend on small sample fractions). With the moderate sample sizes achieved in the separate rotation groups, our tests may have low statistical power, that is, they may fail to reject equality of rotation group estimates because the latter are imprecisely estimated.

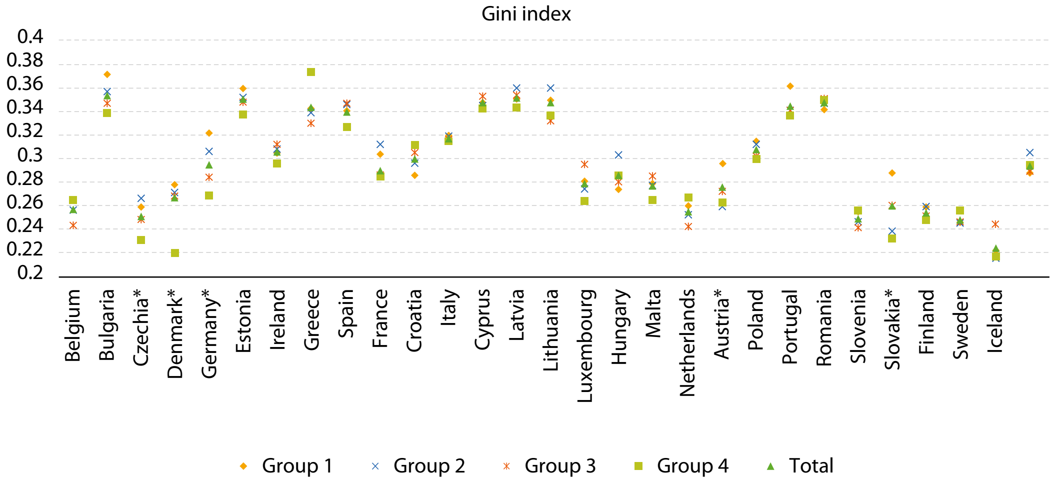
([180]) In a nutshell, the procedure recommended by Eurostat (2016) to construct the cross-section weights is as follows. For each rotation group subsample, the design weights (inverse sampling probabilities at the time of sampling) are adjusted for non-response in the first year and are adjusted for differential attrition (based on observable wave 1 characteristics) in subsequent years. They are also rescaled to account for the potential change in the size of the underlying population due to immigration. In a final step, the four subsamples are combined and the weights of the combined sample may be calibrated to known population totals relative to the survey year to lead to the cross-section weights DB090 and RB050.

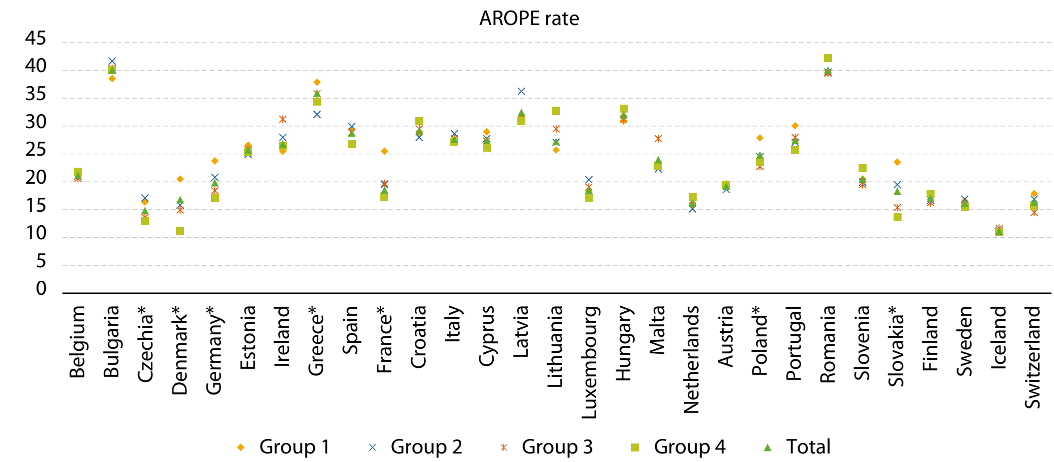
([181]) Our tests are standard Wald tests based on linearisation estimates of the sampling variance of the indicators. Unfortunately, we are not able to account for the full survey design, as much of the relevant information is not available in the UDB. We can only allow for clustering at the household level.

Figure 17.1: Pooled cross-section estimates and rotation group estimates for four social indicators
(%, except for Gini index)









Note: (*) Tests of equality across all four rotation groups rejected at 5 % significance level.

Estimates of indicators are calculated from each of four rotation groups and from the pooled sample. Sample weights are applied. Income definition is equivalised single-person equivalent household income. Only non-negative incomes are used.

Reading note: In Germany, the AROP rate is equal to 19.1 % for the newest rotation group (i.e. group 1) and 13.0 % for the oldest one (i.e. group 4).

Source: Authors' computations, UDB March 2017.

17.4.2. Influence function regression: unconditional and conditional effects

To address concern about the low power of tests of equality of estimates across rotation groups, we turn to IF regression analysis. Results of IF analysis for the four EU indicators are presented by country and for the overall sample in Figure 17.2. In the first stage, we report the UEs estimated through a regression equation containing no further regressors. The figure shows the regression coefficients on three dummy variables identifying observations that belong to the second, third or older rotation group. The reference rotation group (the omitted dummy in the regression) is the first one, and bars mark contrasts between the other rotation groups and this first one in their contributions to the indicators. When estimates by country and for countries considered in this chapter ('Total') are shown, they are based on rescaled IFs (the IF divided by the value of the indicator θ) in order to better compare the IFs for different countries ([182]). For the sake of readability, only UEs with a significance at 5 % level are shown.

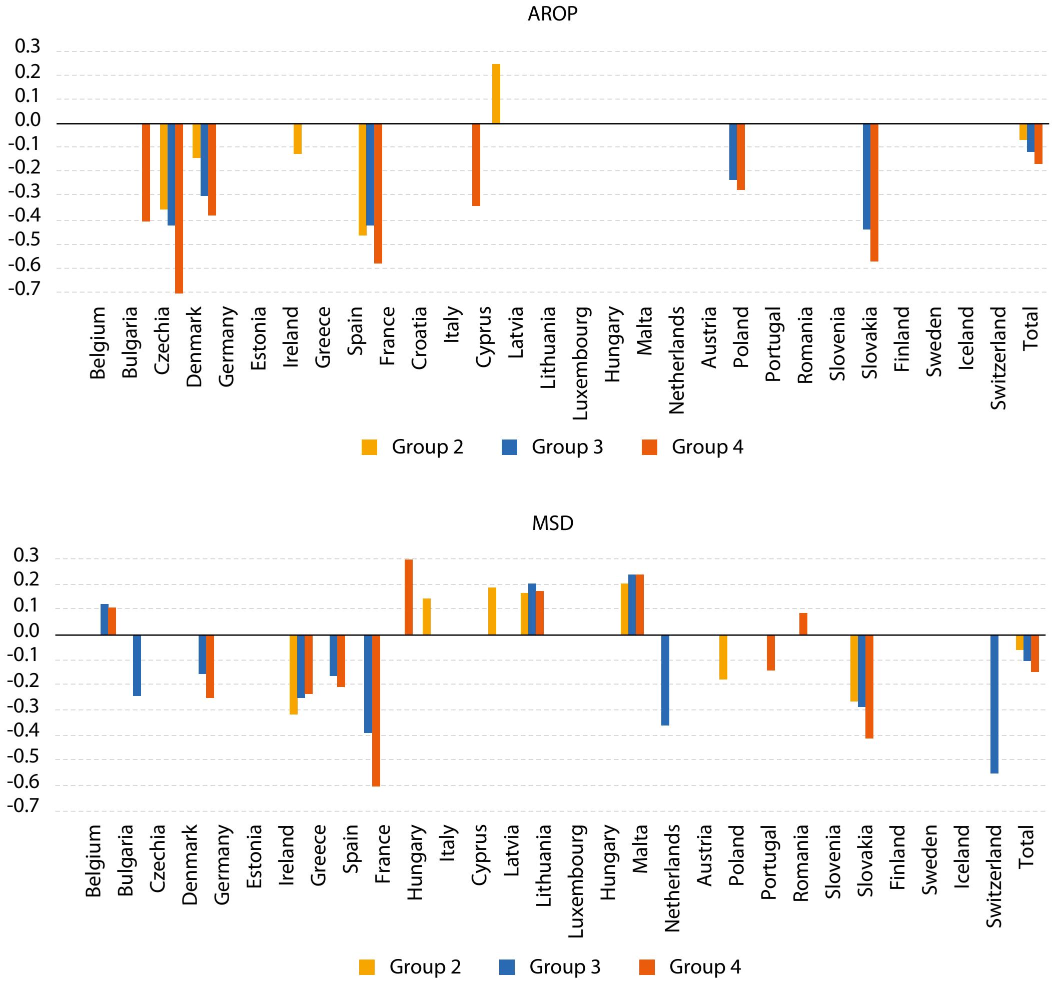
The IF regression results show an overall significant effect of rotational design variables on the Gini index and on poverty and social exclusion measures. In the pooled EU-SILC sample, individuals interviewed at least twice (especially those who have been in the sample for 3 or more years), have a negative contribution on the four social indicators in comparison with those in the newest rotation group. At country level, indication of rotation group bias – in the form of at least one of the three dummy variables being significantly different from zero – appears in 9 countries for AROP, 10 countries for the Gini coefficient, 17 countries for the MSD rate and 11 countries for AROPE. It is the coefficient measuring the contribution of the oldest rotation group dummy that appears most often significant. When significant, the effect is usually negative, as is the case for 8 countries for the AROP rate and 9 for the AROPE. This means that observations from older samples tend to pull estimates of AROP or AROPE downwards compared with the new samples. Results are more mixed for the MSD indicator, for which 10 countries display a negative effect and 7 a positive one.

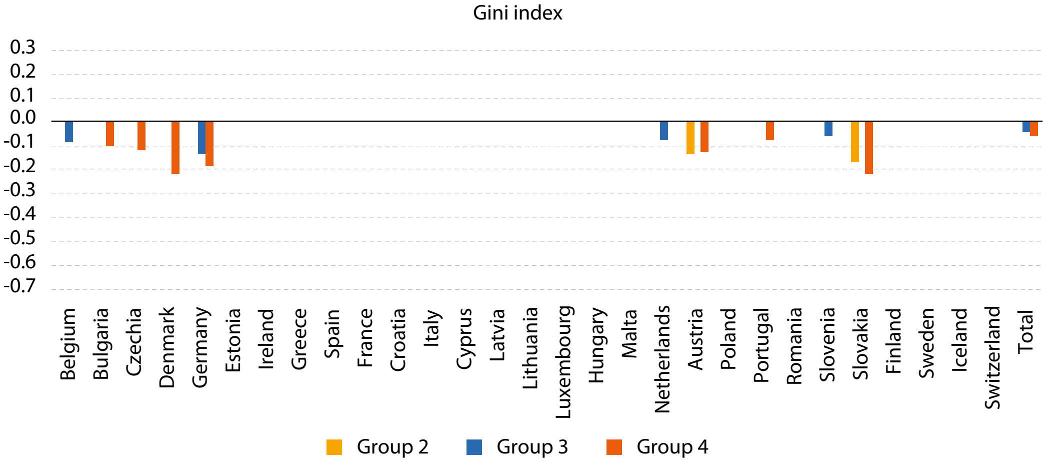
Three countries (Czechia, Germany and Slovakia) always display a negative effect for at least one rotational group, while another five (Denmark, Greece, France, Poland and Portugal) do so for three indicators out of four. Estonia, Iceland, Ireland, Luxembourg, Hungary, Finland and Sweden are the only countries that do not report significant UE coefficients in any of the four indicators. Latvia, Lithuania and Malta display a significant positive effect for two indicators out of four. On the whole, the IF regression approach seems to reveal more evidence of rotation group bias than the simple testing approach of Section 17.4.1.

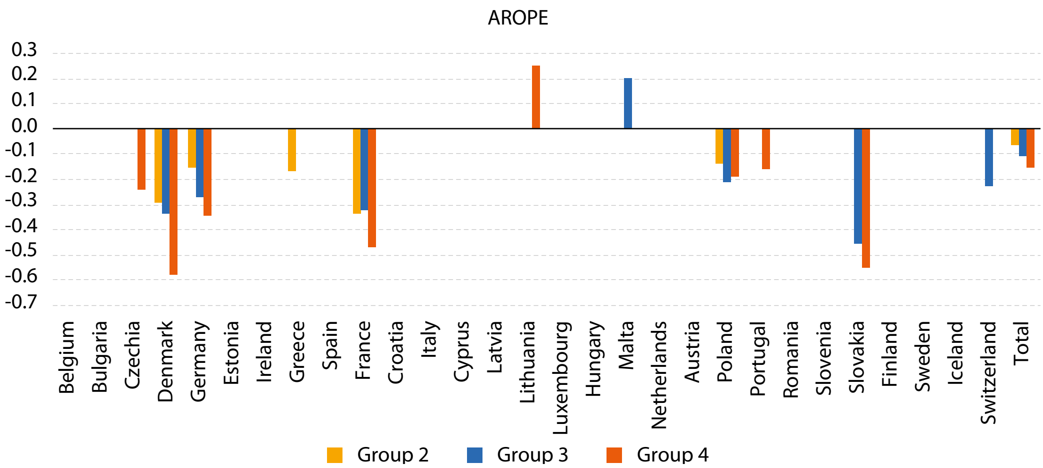
As explained above, one of the possible sources of rotation group effects is differences in the composition of the rotation group samples according to observable characteristics that remain after application of sampling weights. To isolate this effect from other causes such as panel conditioning (i.e. the individual's reaction to being part of a panel), we now examine conditional effects. Conditional effects capture rotation group effects that persist even after we account for differences in a range of household characteristics.

([182]) In the pooled regression analysis, the value of the (scaled) IF used as left-hand side variable is calculated in each country separately.

Figure 17.2: UE estimates on social indicators by country





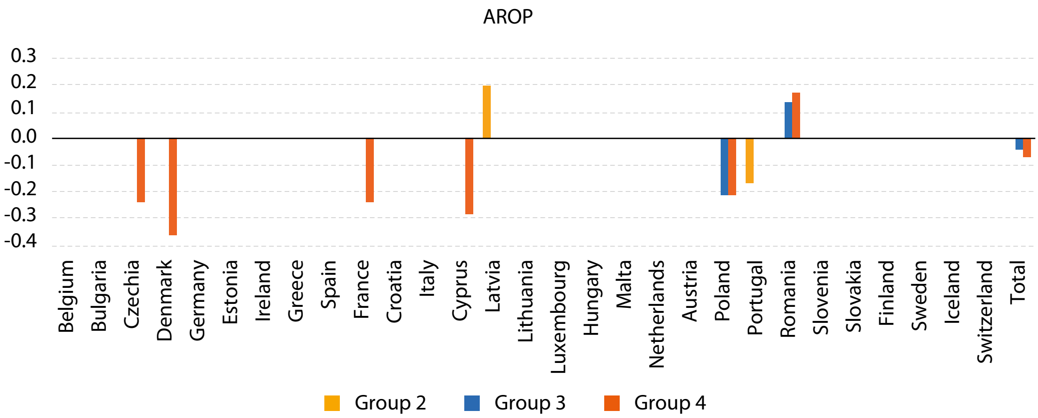


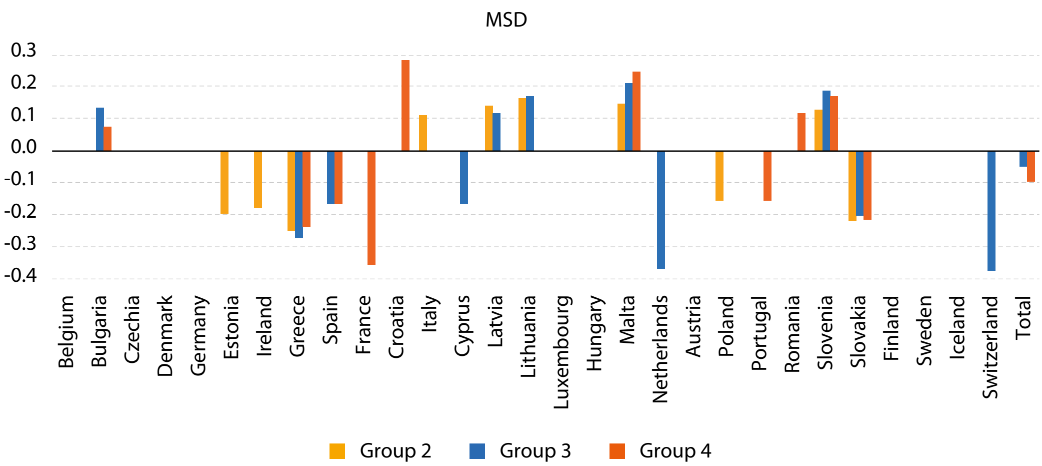
Note: Standard errors are clustered by country and household ID. UEs are weighted with individual sample weights. Only UEs with a significance at 5 % level are shown.

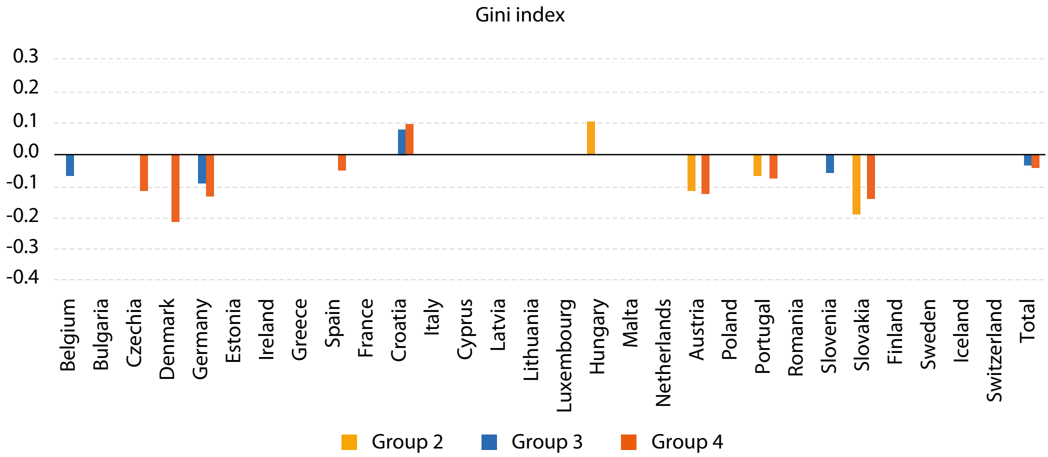
Reading note: UEs are based on scaled influences (IF divided by the point estimate of the indicator).

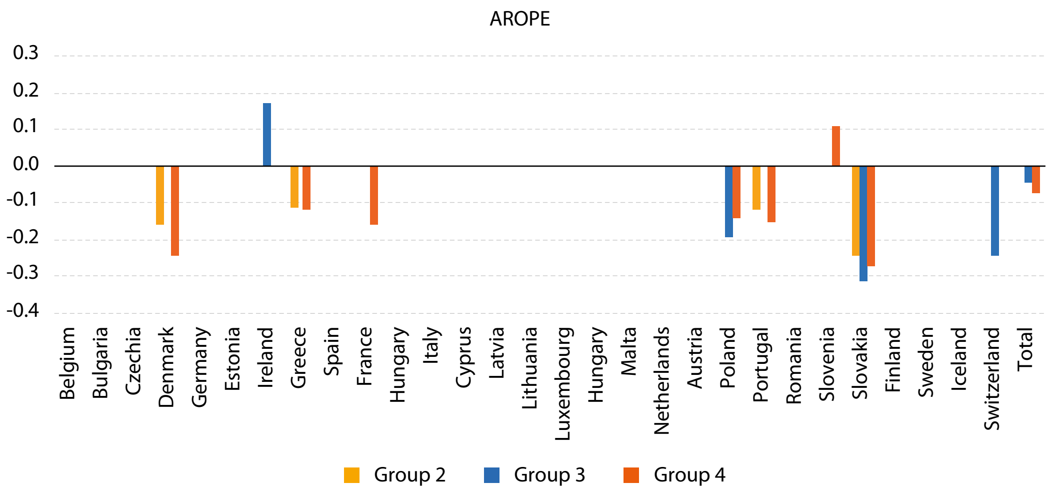
Source: Authors' computations, UDB March 2017.

Figure 17.3: CE estimates on social indicators by country









Note: Standard errors are clustered by country and household ID. CEs are weighted with individual sample weights. Only CEs with a significance at 5 % level are shown.

Reading note: CEs are based on scaled influences (IF divided by the point estimate of the indicator).

Source: Authors' computations, UDB March 2017.

Like Figure 17.2, Figure 17.3 reports regression coefficients on dummy variables identifying the rotation group of sample observations, but the regressions now include additional variables describing a range of household characteristics (see Section 17.3). Figure 17.3 shows that including covariates for characteristics of households in IF regressions does not eliminate evidence of rotation group bias. The contributions of observations from different rotation groups often still vary. This points towards panel conditioning or attrition driven by variables not included in the covariates, rather than change in sample composition along our conditioning variables, as a source of rotation group bias. By the same argument, change in the underlying population due to immigration does not seem to be a key driver of the rotation group bias, since we include the nationality of household head as a conditioning variable – a variable closely correlated with migration status.

CEs remain overall significantly negative on estimates of the four social indicators – the case of the MSD rate being still more mixed – even though coefficients are unsurprisingly lower than UE ones and effects of being in the second rotation group (i.e. 2 years in the survey) disappear. Similarly, magnitudes of conditional impacts at country level decrease relative to the unconditional ones but remain overall significant at 5 %. Portugal always has a significant negative effect, while Iceland, Luxembourg, Finland and Sweden never display a significant effect.

17.4.3. Can we link rotation group bias to survey design characteristics?

Our analysis reveals that estimates for a number of countries exhibit rotation group bias: different rotation groups influence social indicators estimates differently. But not all countries are affected. We find frequent rotation group effects for Czechia, Germany, Portugal and Slovakia, and to a smaller extent for Denmark, Greece, France and Poland. Eurostat provides guidelines for the collection of the data, but Member States still have a degree of freedom in the implementation of the instrument. Can we relate the presence of rotation group biases to any of the survey design characteristics implemented in those countries? We consider three broad design characteristics: (1) the source of the sampling frame; (2) the sampling unit; (3) perhaps most importantly, the income data collection method. In addition, migration was mentioned earlier as being a potential explanation of the rotation group bias, as it constitutes a change in the underlying population (see Section 17.1). We therefore also analyse here whether or not the rotation group bias is associated with migration inflow as measured by the number of migrants per 100 000 inhabitants (Eurostat, 2020).

For the source of the sampling frame, most countries use administrative population registers, while others draw samples from national censuses. Administrative registers are normally continuously updated and should better reflect the population at any given point in time. This means that samples drawn in different years from administrative registers – different rotation groups – may conceivably differ because of changes in the population covered. In contrast, samples drawn from censuses, which are updated less frequently, are possibly less up to date with the target population but should not be affected by changes in the sampling frame.

For the sampling unit, participating countries can opt for individuals, households or dwellings/addresses. A priori, the choice of sampling unit is least likely to be related to the risk of rotation group bias. The choice, however, has implications for the follow-up of respondents over time, in particular about how co-residents are treated in the event of household composition changes over time (Iacovou and Lynn, 2017). This may conceivably influence changes in a rotation group's sample composition in follow-up interviews over time.

Finally, some countries collect income data directly from administrative registers ('register countries'), whereas others collect them from household interviews ('survey countries') ([183]). The former is expected to improve the accuracy of income reports and reduce non-response (by reducing the burden on interviewees). Panel conditioning, or 'learning effects', should not be observed with regard to

([183]) By contrast, note that all countries collect the MSD variables using a questionnaire.

income data in register countries, which reduces the possibility of rotation group bias through this channel. Note that the use of registers is normally coupled with the use of the individual as the sampling unit, although this may not be true of countries that shifted from survey interviews to register collection after the onset of EU-SILC (Törmälehto et al., 2017).

On the basis of the information from Eurostat (2016) about the EU-SILC methodology and national quality reports, we classified countries participating in EU-SILC as shown in Table 17.2.

To assess if these design features have any impact on the presence of rotation group bias, we ran the pooled cross-country IF regressions separately by subgroups of countries classified by design char-

Table 17.2: EU-SILC countries by main characteristics of the sampling design

Country	Source of sampling frame		Sampling unit			Income data collection	
	Population registers	Census	Individuals	Households	Dwellings/ addresses	From registers	From interviews
Belgium	X			X			X
Bulgaria		X		X			X
Czechia	X				X		X
Denmark	X		X			X	
Germany	X				X		X
Estonia		X		X		X	
Ireland		X		X		X	
Greece		X		X			X
Spain	X				X	X	
France		X			X	X	
Croatia		X			X		X
Italy	X			X		X	
Cyprus		X		X		X	
Latvia	X				X	X	
Lithuania	X			X		X	
Luxembourg	X				X		X
Hungary		X		X			X
Malta		X		X			X
Netherlands	X				X	X	
Austria	X				X	X	
Poland	X				X		X
Portugal		X			X		X
Romania		X			X		X
Slovenia	X		X			X	
Slovakia		X		X			X
Finland	X		X			X	
Sweden	X		X			X	
Iceland	X		X			X	
Switzerland	X			X		X	

Reading note: Belgium uses administrative population registers as the source of its sampling frame, whereas Bulgaria draws its sample from national censuses.

Sources: Eurostat (2016) and national quality reports.

acteristics (as per Table 17.2). Table 17.3 reports the *p*-values of F-tests of joint significance of the rotation group dummies in these regressions, which also include controls with household characteristics.

Results illustrated in the first two columns point out that, except for MSD, the rotation group bias is more common in countries using population registers as the source of the sampling frame, but largely disappears where a census is the sampling frame. This may be related to the fact that sampling from the updated registers increase demographic differences among rotation group members. Regressions by type of sampling unit show that the rotation group bias on social indicators is present when the sampling units are dwellings or addresses, but disappears when the sampling unit is the individual or a household, which may be due to easier follow-up of observations. Regressions by the income data source show mixed results. Comparing estimates by income data collection should make it possible to isolate the learning process effect, because that effect is observable only in those countries that collect incomes from interviews. However, most countries that use registers also adopt the selected respondent design, which in turn is associated with larger attrition rates (Jenkins and Van Kerm, 2017). A rotation group bias takes place on the Gini index in countries imputing income from registers, whereas its effect is significant on the MSD indicator in the other countries. These results do not support the learning effect as the dominant driver of the rotation group bias, since such learning should not happen when registers are used to collect income information. This leaves attrition driven by variables not controlled for in our analysis as a main suspect for the rotation group bias. Yet, overall, the connection between evidence of rotation group bias and design characteristics appears mixed in our analysis. This was already observed by Glaser et al. (2015). Finally, we see from the last column of Table 17.3 that rotation group bias remains present when we add controls for annual immigration rates. This suggests that immigration – and therefore changes in the target population – cannot explain the rotation group bias either.

Table 17.3: ***p*-Values for F-tests of joint significance of rotation group dummies in pooled IF regressions by survey design characteristics (columns 2–8) and when adding annual immigration levels as control (column 8)**

Social indicator	Source of sampling frame		Sampling unit			Income data collection		Migrants per 1 000 inhabitants
	Population registers	Census	Individuals	Households	Dwellings/ addresses	From registers	From interviews	
AROP rate	0.003	0.680	0.685	0.712	0.001	0.120	0.265	0.105
Gini index	0.000	0.760	0.263	0.923	0.000	0.000	0.206	0.000
MSD rate	0.190	0.000	0.311	0.274	0.000	0.869	0.000	0.001
AROPE rate	0.000	0.162	0.665	0.902	0.000	0.212	0.083	0.006

Note: Pooled IF regressions on rotation group maturity dummy variables, including sociodemographic variables (and immigration rates for column 8) as additional controls. Cross-sectional sample weights are applied.

Reading note: The *p*-values are for joint tests that all three rotation group indicators are zero.

Sources: Authors' computations, UDB March 2017. Migration statistics were taken from Eurostat website (online data codes: migr_imm1ctz and migr_pop1ctz).

17.5. Conclusion

The aim of this chapter is to examine whether or not the rotational design of EU-SILC affects the estimates of social indicators, such as income poverty, inequality or social exclusion. Our application of IF methods to the 2014 EU-SILC suggests that there is a rotation group bias in social indicators in a relatively large number of cases (countries or indicators). The econometric results show significant effects of rotation group identifiers on income inequality and poverty measures. The magnitude of our estimates is sometimes large. For example, we have observed differences of up to 10 p.p. in the AROPE rate measured across different rotation groups in some countries – a 100 % relative difference between two different rotation groups. The optimistic reaction to these findings would be that rotation group bias turns out to be absent in the majority of cases. The pessimistic view would be that rotation group bias is present in a non-negligible number of cases and may remain a source of concern. Individuals interviewed at least twice (and especially those who have been in the sample for 4 years) tend to drag levels downwards for the four social indicators considered, compared with individuals interviewed for the first time. In other words, the respondents who remain in the sample appear, on the whole, to be better off than those who have just entered the survey, and this has a significant impact on most social indicators. Sampling weights do not appear to make rotation groups indistinguishable from each other with regard to their contribution to social indicators, and the findings point towards learning effects and/or attrition based on unobserved characteristics as potential drivers of the bias. This may be a source of concern regarding the reliability of EU social indicators. It can also lead to inconsistencies between estimates drawn from the longitudinal EU-SILC data sets and those drawn from the cross-sectional EU-SILC data sets. Recent literature has shown that similar problems exist in the measurement of unemployment (Krueger et al., 2017).

What can be done? Although additional analysis of the effects of sampling design characteristics is needed to better understand the nature of the problem – in particular about the best combination of register data and selected respondent versus household sampling – sample weights seem to be a natural way to address concerns about rotation group bias. Further research could see if IF regression, for example, could be exploited in the calculation of sampling weights directly when we need to estimate distributive measures as social indicators. More practically, evidence of rotation group bias serves to highlight the key importance of ensuring follow-up over time and of minimising attrition. Monitoring the presence of rotation group bias in key social indicators derived from EU-SILC is simple and should be part of routine EU-SILC data validation processes.

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18

The measurement of social class in EU-SILC: comparability between countries and consistency over time

Tim Goedemé, Marii Paskov and Brian Nolan ([184])

18.1. Introduction

Across the social sciences, social class is seen as a key indicator of socioeconomic stratification. The social class literature postulates that in market economies it is position in the labour market and occupation that fundamentally determine social and economic inequalities (Goldthorpe, 2007; Rose and Harrison, 2010). Individuals higher up in the social class hierarchy are assumed to enjoy a range of economic advantages, including economic security, economic stability and better long-term economic prospects (Bukodi and Goldthorpe, 2019; Erikson and Goldthorpe, 1992; Goldthorpe, 2007; Goldthorpe and McKnight, 2006). Since social class shapes access to economic resources and advantages, it has been linked with a range of further outcomes, including health (Richards and Paskov, 2016; Shaw et al., 2014; Marmot et al., 1997), life satisfaction (Lipps and Oesch, 2018) and voting behaviour (Brooks and Svallfors, 2010; Evans, 1999), to name a few. Although the 'death of class' argument suggests that social class has lost its relevance as a determinant of economic standing (Clark and Lipset, 1991), numerous recent studies find that social class still shapes economic outcomes in life (Albertini, 2013; Williams, 2017; Wodtke, 2016). Social class thus remains a highly relevant concept for the social sciences.

The importance of class as a social science concept is illustrated by the fact that most social science surveys in Europe include the information required to assign individuals or households to social class positions, most typically the Erikson–Goldthorpe–Portocarero schema or the ESeC schema (Connelly et al., 2016). Considering that EU-SILC is very rich in data on living conditions and also contains the basic variables to reproduce ESeC (although with some noticeable caveats, as will be discussed in this chapter), it presents an opportunity to study class inequalities or the effect of social class on a range of outcomes, including earnings, household income, poverty, material deprivation, economic stress, housing conditions, labour market conditions and health, with a degree of detail that is not possible with other surveys. A review of the literature indicates that the primary focus of comparative studies utilising social class information in EU-SILC (and its precursor, the ECHP) has been the relationship between social class and economic vulnerability, including poverty and material deprivation (Bedük, 2018; Maître et al., 2012; Paskov et al., 2018; Pintelon et al., 2013; Whelan and Maître, 2010, 2012; Whelan et al., 2014, 2013; Watson et al., 2010, 2018). Recently, two studies have used EU-SILC to investigate the association between social class and earnings in a comparative perspective (Albertini et al., 2020; Goedemé et al., 2020). Other studies have used EU-SILC to look at class inequality in housing tenure and housing well-being (Filandri and Olagnero, 2014) or class inequality in health (Chauvel and Leist, 2015).

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Although a number of published papers have used social class measures in EU-SILC, we are convinced that several of the measurement issues regarding social class have received insufficient attention. Therefore, in this chapter we discuss the measurement of class, as operationalised by ESeC, in EU-SILC. Furthermore, we illustrate the relevance of social class, and some of the associated data challenges, by looking into the level of in-work poverty experienced by people of different social classes across the EU in the period covered by EU-SILC, 2004–2018. The prior work cited above has shown that social class is one of the important factors associated with poverty but that the strength of the association varies across countries. One study shows that class inequalities are stronger in less prosperous countries (Whelan and Maître, 2012). In another study, Whelan and Maître (2010) show that the relative risk of income poverty is highest for the small farmer and petit bourgeois classes, and lowest for the salariat class, a finding that holds across all welfare regimes, although to varying degrees.

In what follows, we first explain ESeC and how it can be implemented in EU-SILC, albeit with some caveats (Section 18.2). Subsequently, we briefly discuss some other methodological issues related to analysing EU-SILC (Section 18.3), before turning to our findings (Section 18.4). We first highlight the social class structure of those in paid work across Europe and illustrate how several limitations to the consistency of the occupational variable impacts upon the social class structure across countries and time. Thereafter, we do the same for levels and trends in in-work poverty by social class. We conclude with a brief summary of the main findings and some suggestions for further improving the quality of EU-SILC in the future.

18.2. The European Socio-economic Classification in EU-SILC

18.2.1. Background of the European Socio-economic Classification class schema

ESeC is a categorical social class schema that was developed more than a decade ago to facilitate comparative research on social class in Europe (Rose and Harrison, 2007). In the ESeC schema, class positions are differentiated in terms of two central elements: employment status and employment contracts typical for different occupations (Erikson and Goldthorpe, 1992). Employment status tells us whether someone buys and controls the labour of others (employers), sells their own labour directly to customers and clients (self-employed), or sells their labour to employers and employing organisations (employees). In the last group, employees, who constitute the largest share of the labour force, an additional distinction is made depending on the nature of their employment contracts, which is deduced from their occupation. A 'labour contract' is typically applied to occupations that require relatively low-level, unspecialised and widely available capacities and skills (i.e. manual and routine non-manual occupations). A 'service contract', however, is applied to occupations in which employees typically exercise delegated authority or specialised knowledge and expertise on behalf of their employers (i.e. managerial and professional occupations). Furthermore, mixed forms of employment contracts are applied to occupational positions that are found between these two extremes.

Occupation is usually measured on the basis of ISCO ([185]), while those voluntarily out of paid employment are considered a separate category. Since ESeC is often not readily available in surveys, it needs to be constructed by researchers themselves. EU-SILC offers many of the variables required to construct ESeC, but the level of detail, quality and exact definition varies quite substantially across countries and over time. Furthermore, in 2011 EU-SILC moved from ISCO-88 to the ISCO-08 classification of occupations. Given that the two classifications do not perfectly map onto each other, a break in series occurs. Luckily, for most countries both types of classifications are available for at least 1 year, so it is possible to compute overlapping time series (with the exception of Bulgaria, Ireland and Finland, for which ISCO-88 is missing in 2011). We refer to ESeC based on ISCO-88 as 'ESeC-88' and ESeC based on ISCO-08 as 'ESeC-08'.

18.2.2. Constructing the European Socio-economic Classification in EU-SILC

The various social classes distinguished in ESeC and the way ESeC is operationalised in EU-SILC are illustrated in Figure 18.1. We build strongly on the work of Anika Herter and Heike Wirth (Gesellschaft Sozialwissenschaftlicher Infrastruktureinrichtungen (GESIS)) to compute ESeC in EU-SILC, with a number of minor tweaks ([186]).

In a first step, a distinction is made between the self-employed and employees, by making use of variable PL040 (status in employment). For those with a missing value on PL040, we complete this variable with information from PL031 (self-defined current economic status), for the period for which ISCO-08 is available ([187]). In contrast to the original code by Herter and Wirth, we make a further distinction between self-employed with and without employees, before moving to the next step. We do so because a substantial number of self-employed people indicate having no employees but appear to be working in large economic units. In addition, we keep the distinction between employees and family workers.

Subsequently, the self-employed are subdivided by the number of people working at their local economic unit (variable PL130), while employees are split up by whether or not they are in a supervisory position (PL150). Given that PL150 is not available for family workers, we assign them all a non-supervisory status (in the GESIS code, family workers receive a missing value, and are subsequently excluded from the computation) ([188]).

In the next step, everyone is assigned to one out of nine social classes. Figure 18.1 illustrates this process for ESeC-88 (it is slightly different for ESeC-08). Self-employed people with at least 10 employees are directly assigned to class 1. The other categories are assigned to each class based on their ISCO occupation (PL050, PL051). Self-employed people without employees or those with fewer than 10 employees may be assigned to class 1, 2, 4 or 5 depending on their occupation. Employees are assigned to category 1, 2, 3, 6, 7, 8 or 9, depending on their supervisory role and occupation. Whereas those with a supervisory role only end up in class 1, 2 or 6, those without such a role can end up in any class, except for classes 4 and 5. This procedure is

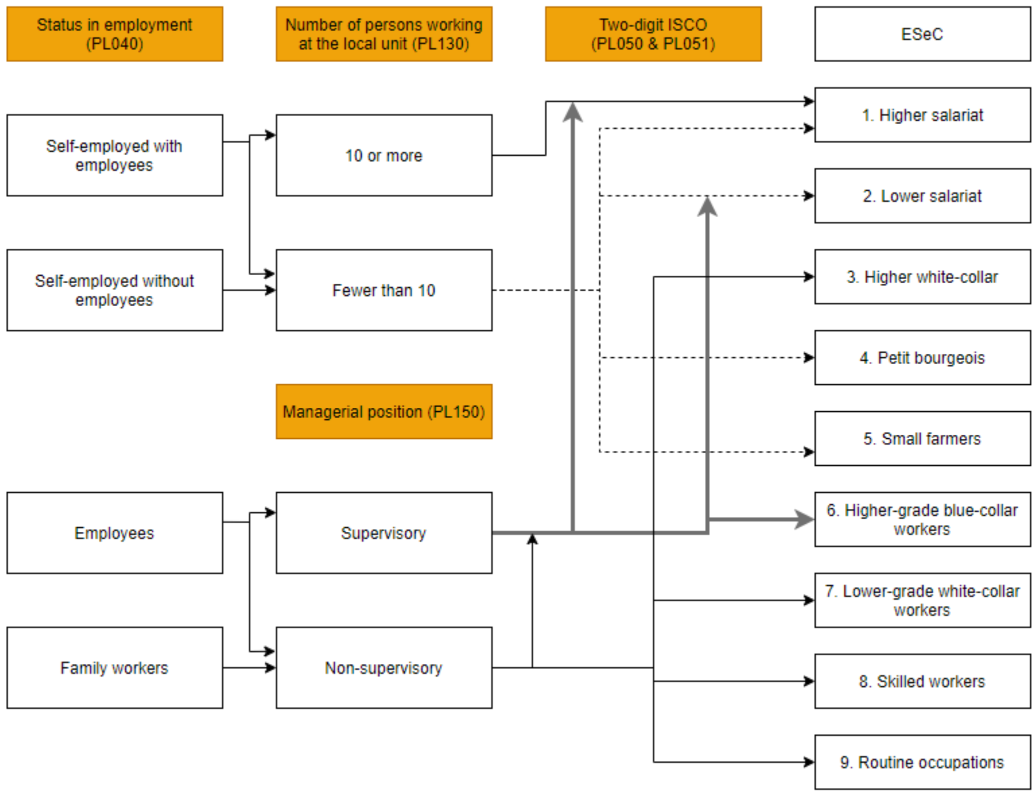
([185]) See the ILO website (https://www.ilo.org/public/english/bureau/stat/isco/, accessed 19 June 2019).

([186]) Herter and Wirth developed Stata do-files by EU-SILC year (up to EU-SILC 2014), following the instructions of Rose and Harrison (2007). These do-files can be downloaded from the GESIS website (https://www.gesis.org/en/gml/european-microdata/eu-silc/, last accessed 30 June 2020). We integrated the computation of ESeC for all SILC years into a single Stata do-file, with the modifications mentioned in the text. The do-file is available from Tim Goedemé (https://timgoedeme.com/tools/esec-in-eu-silc/). Recently, the iscogen command in Stata created by Ben Jann has become available to automatically construct different versions of class variables, including ESeC. However, we did not test how iscogen differs from our own code.

([187]) We only do this for the second period onwards, as PL031 was only introduced in 2009, and we do not want to add another break in series as well as the one that occurred when changing from ISCO-88 (PL050) to ISCO-08 (PL051). PL031's predecessor PL030 does not make a distinction between employees and the self-employed.

([188]) A more nuanced approach regarding the supervisory status of family workers might be to consider them supervisors if there are more than two persons in the local economic unit. However, we stick to our simple approach because (1) the alternative might lead to other misclassifications; (2) the share of family workers is less than 1 % of the labour force; (3) the alternative would result in different social classes for only 1 % of family workers (so it would not affect the overall results). Further research should clarify what would be the best way to classify family workers, for instance by taking into account their partner's supervisory status in the business or the size of the local economic unit (presumably the size of the family business).

Figure 18.1: Flowchart to illustrate the code to reconstruct ESeC-88 in EU-SILC



Note: The procedure is somewhat different in the case of ESeC-08 (making use of PL051): some large employers are assigned to classes 3 and 5, while some self-employed people with fewer than 10 employees are also assigned to class 3. Furthermore, some non-supervisory employees are assigned to class 5, and no single non-supervisory employee is assigned to class 6 any longer.

Source: Own compilation based on GESIS Stata do-files (see text).

rather complex, as the four groups formed in the previous step may end up in various social classes depending on their occupation, and people with a similar ISCO occupation may be assigned to different social classes, depending on the group to which they belonged in the previous step. For example, the first class 'Higher salariat' may include self-employed people with at least 10 employees, self-employed people with fewer than 10 employees (including those without any employee), or employees with or without a supervisory role, depending on their ISCO occupation.

18.2.3. Limitations of constructing the European Socio-economic Classification in EU-SILC

There are some important general limitations to the variables available in EU-SILC for constructing the ESeC, as well as specific issues that limit their comparability across countries and within countries across time. Next, we briefly highlight the most important caveats (for an extensive discussion, see Goedemé, 2019).

Sample selection

An important limitation is that some information is only available for selected respondents in countries with the selected respondent model (based on PX040, the selected respondent status), considerably restricting the sample size in these countries. Furthermore, data availability for the unemployed varies strongly across countries and in some countries also across time (as measured by PL030 and PL031). Therefore, for comparative studies it is best to limit the analysis to the population currently at work, as otherwise the composition of individual classes will be affected by partial data availability, probably for a group with a specific income profile ([189]).

Occupational information

Another limitation is that the ISCO classification is only available at two-digit level, whereas in its original design ESeC was refined up to three digits of ISCO. Rose and Harrison (2007) show for the first round of the ESS that making use of a two- rather than a three-digit categorisation misclassifies about 14 % of cases. For Malta, ISCO is even available only at one-digit level, and this is also the case for some years for Germany and Slovenia (also affecting comparability across time). Similarly, for Ireland and Slovakia (until 2014) ISCO-08 is available in about 25 rather than 42 categories, and it is not clear what grouping has been applied. As mentioned earlier, a general break in series takes place in 2011 when moving from ISOC-88 to ISCO-08, although this is generally accompanied by an increase in precision of the coding of ISCO (going from about 26 or 27 categories to about 42). For EU-SILC 2011, it can be observed that, for all countries combined, the change affects the classification of 13 % of (unweighted) cases when applying a three-class schema (comprising classes 1 and 2, 3–6 and 7–9).

Non-response

Furthermore, comparability both across countries and within countries over time is challenged by relatively strongly fluctuating rates of non-response. Overall, among the working age and currently in work sample, social class is generally available for well over 90 % ([190]). An exception is France, where in many survey years social class is available for fewer than 90 % of this group. However, in some countries the response rate for social class fluctuates considerably, including in Austria (2007–2008), Denmark (2006, 2007, 2014, 2015), Finland (2004, 2007), France (2008, 2011, 2012), Hungary (2006, 2017), the Netherlands (2006), Norway (2011, 2012) and Sweden (2012) ([191]). In Iceland social class is not available from EU-SILC 2014 onwards, and in Slovakia it is not available for 2018 ([192]). In many cases, non-response does not seem to be random, and may severely affect the composition of social classes. For instance, among those for whom data are available, the percentage of self-employed in the highest classes is equal to 100 % in Finland in 2004, while the self-employed are completely missing from the picture in Denmark from EU-SILC 2012 until 2015 (owing to missing information on PL130). Other non-negligible changes driven by non-response in the share of the self-employed in the upper classes are observed in countries such as Austria (2007–2008), Bulgaria (2008), Hungary (2010, 2014), Slovakia (2012) and Sweden (2006, 2010, 2012). Furthermore, in Denmark throughout the entire period, and in Sweden until EU-SILC 2011, the availability of ESeC for the self-employed is close to or below 50 %, and in Slovenia until 2011 it is about 80 %. Therefore, it is recommendable to analyse differences by social class excluding the self-employed, and be cautious about studying trends over time when the self-employed are included in the analysis. A preliminary analysis for a selection of countries shows that, overall, average earnings tend to be lower among non-respondents, while earnings inequality within this group is higher than in those for which social class is available (see Goedemé, 2019).

([189]) However, for specific countries or years it should be possible to do a reliable class analysis for the unemployed.

([190]) In selected respondent countries, this is if the sample is restricted to selected respondents.

([191]) Years in brackets indicate a big change in the non-response rate compared with surrounding years.

([192]) PL051 is filled in for fewer than 10 cases.

18.3. Other methodological issues

We use the 2020 spring release of EU-SILC, with data from the 2004 up to the 2018 wave. With the exception of Finland, for most countries the 2004 data quality regarding ESeC does not seem worse, and in some cases (notably Sweden) it even seems better than EU-SILC 2005. 'Official' breaks in series (i.e. as reported on the Eurostat data portal for the AROP threshold) include those in Bulgaria (2016), Luxembourg (2016), the Netherlands (2016), Sweden (2008), and the United Kingdom (2017) ([193]). It is somewhat surprising that other changes in data collection or weighting procedures are not counted as breaks in series, e.g. the change in underlying data source for the United Kingdom in 2012 ([194]), the change in weighting schemes in Belgium since 2012, and the increased use of register data for collecting income information for a range of countries (see, among others, Zardo Trindade and Goedemé, 2020).

In all our analyses, we include both employees and the self-employed, and highlight problems with changing shares of self-employed when relevant. We follow the standard procedure for computing the AROP rate (but do not make use of the RX variables on equivalised disposable income or poverty status provided with the data by Eurostat). We compute standard errors and confidence intervals taking the sample design into account as much as possible (see Goedemé, 2013) ([195]). The Stata do-files that we created for this chapter, and the detailed results in Excel, are available online ([196]).

([193]) See the Eurostat online database (code ilc_li02; https://tinyurl.com/yaky6qr6, accessed 8 July 2020).
([194]) In 2012 the Family Resources Survey replaced the General Lifestyle Survey as the main source for EU-SILC; see, for instance, https://beta.ukdataservice.ac.uk/datacatalogue/series/series?id=200015#!/faqs (accessed 19 June 2019).
([195]) More information and Stata do-files available on Goedemé's website (https://timgoedeme.com/eu-silc-standard-errors/, accessed 8 August 2020).
([196]) https://timgoedeme.com/tools/esec-in-eu-silc/ (accessed 8 August 2020).

18.4. Findings

18.4.1. The class structure of the population currently at work

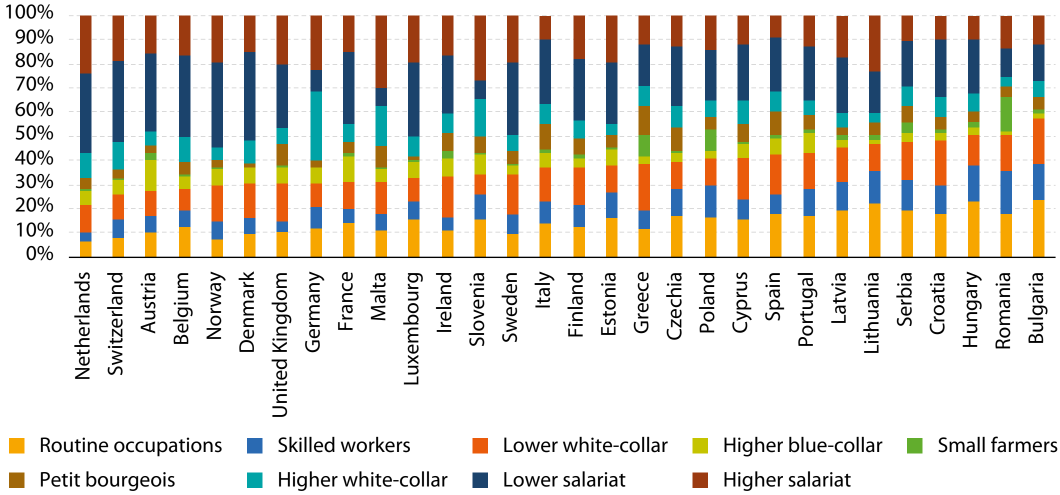
Before we delve into the income situation of social classes across Europe, Figure 18.2 illustrates the relative share of social classes in the population at working age (i.e. between 18 and 65 years old) and currently at work. Figures are based on EU-SILC 2018. The countries in the graph are ordered by the joint share of the 'Routine occupations', 'Skilled workers' and 'Lower white-collar' classes ([197]). European countries vary quite substantially in the class structure of their workforce. The joint share of the lower three classes in each country appears to be negatively correlated with median income (in PPS). While the lower classes account for less than one third of the working population in rich countries such as the Netherlands, Switzerland, Austria and Belgium, their share is well over 40 % in Bulgaria, Romania, Hungary, Croatia and Serbia. Conversely, the share of the upper two classes (the higher and lower salariat) in the richest countries is around 50 % of the population at work, whereas the equivalent figure is 30 % in the poorest countries of Europe. Germany is a notable exception, probably because of less precise data (see Figure 18.4 and discussion below). A distinct category consists of the 'Petit bourgeois' and 'Small farmers'. While small farmers account for fewer than 2 % of those at work in the great majority of countries, their share is above 8 % in Greece and Poland and close to 15 % in Romania. The share of those categorised as belonging to the petite bourgeoisie varies more gradually, reaching close to 10 % in Malta, Czechia, Spain, Italy and Greece.

In many countries, the class structure has changed over time, although mostly gradually. The trends that stand out most are the expansion of the higher salariat and the declining share of the skilled workers, especially in the first period (i.e. until SILC 2011). These trends are strongest in Iceland, Latvia, Bulgaria, Lithuania, Romania and Austria in the

([197]) In this chapter, we use the terminology adopted by Rose and Harrison (2007) to describe the various classes identified by ESeC.

Figure 18.2: Share of each social class in the population at working age and currently in paid work, by country, 2018

(%)



Note: Countries ordered by the joint share of the routine occupations, skilled workers and lower white-collar classes. Germany, Malta and Slovenia: based on first digit of ISCO-08. Data for Slovakia are missing.

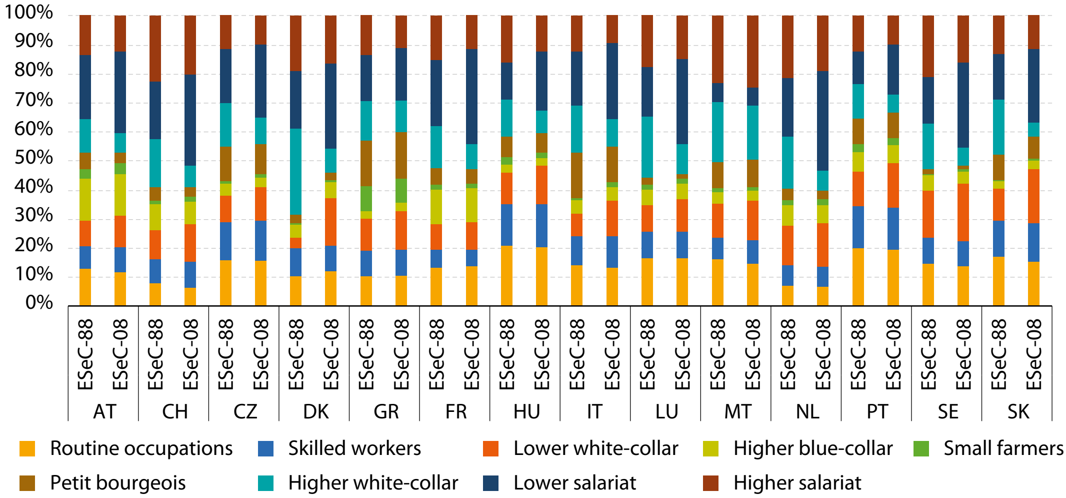
Reading note: In Latvia about 20 % of those of working age and currently at work belong to the routine occupations class.

Source: Authors' computations, UDB March 2020.

first period, and Luxembourg and Austria in the second period (i.e. from SILC 2011 onwards). The most noticeable exceptions that display the opposite trends are Belgium and Croatia (only the first period). In both the first and the second period, in Hungary and Slovakia the shares of both the higher salariat and the skilled manual class decrease. It is worth remarking that in many countries these changes were smaller than the ones caused by the transition from ISCO-88 to ISCO-08 (see Figure 18.3). In nearly all countries this transition resulted in a sizeable expansion of the estimated share of the lower salariat, at the expense of the share of the higher salariat and higher white-collar classes. That can be problematic, given that most common groupings of social classes keep higher white-collar and lower salariat in separate categories (see Rose and Harrison, 2007). The share of the routine occupations, skilled manual and lower white-collar classes was not so much affected by the transition in ISCO codings, although also in these cases a sizeable share of the sample is reallocated to a different class, without affecting the overall share of these classes much.

Another major change in some countries is related to the varying degree of precision of the ISCO coding. In Germany, Malta and Slovenia, the move from two-digit to one-digit ISCO codes has led to quite a drastic change in the estimated social class structure of those at work, resulting in a considerable overestimation of the share of the higher white-collar and higher salariat classes, at the expense of the lower salariat class's share. Similarly, the move from 25 to 40 categories in Ireland in EU-SILC 2018 resulted in a sizeable change in the share of the skilled manual and lower white-collar classes. In contrast, a similar move from 27 to 41 categories from EU-SILC 2015 onwards in Slovakia appears to have had only a minor impact on the share of social classes among those at work (see Figure 18.4).

Figure 18.3: Change in class composition of the population of working age and currently in paid work when moving from ISCO-88 to ISCO-08, selected countries, 2011
(%)



Note: Selection of countries.

Reading note: In Denmark the share of higher white-collar workers is much higher when using ISCO-88 than using ISCO-08 for constructing the social class variable.

Source: Authors' computations, UDB March 2020.

Figure 18.4: Change in the class composition of the population of working age and currently in paid work for countries with changing precision in ISCO coding, EU-SILC 2007–2018
(%)

Note: When data are available, the last 2 years before the change in precision and the subsequent 2 years are shown.

Reading note: The reduction in the precision in ISCO coding in Germany coincided with a strong reduction in the share of the lower salariat and a strong increase in the share of the class of higher white-collar workers in the population of working age and currently in paid work.

Source: Authors' computations, UDB March 2020.

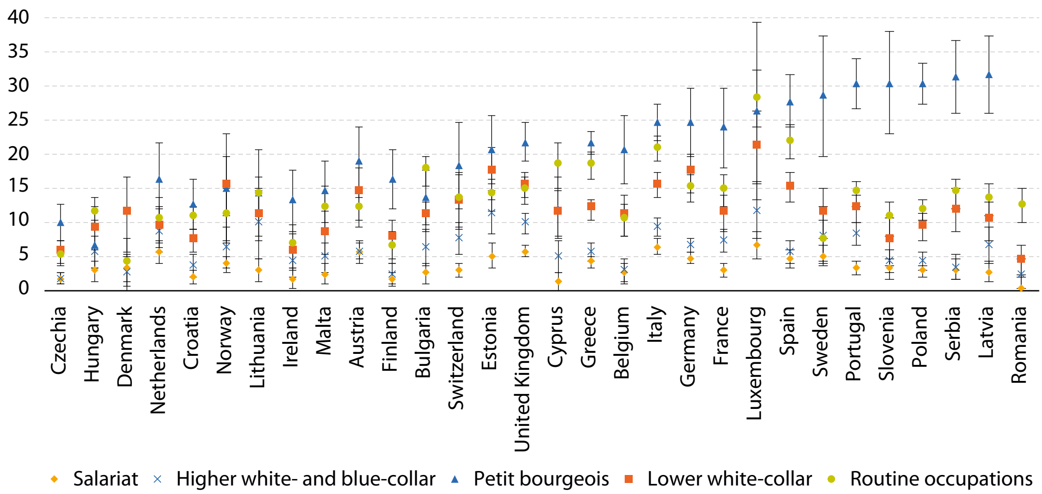
18.4.2. In-work poverty by social class in 2018

Social class is known to be associated with an entire range of outcomes in life (see Section 18.1). This also applies to poverty outcomes. As is shown in Figure 18.5, a clear social class gradient in the AROP rate is found in many countries. To facilitate the presentation and avoid small cell sizes, we combined classes into five groups, in line with the recommendations by Rose and Harrison (2007): (1) the higher and lower salariat (category 'Salariat'); (2) the higher white-collar and higher blue-collar workers ('Higher white- and blue-collar'); (3) the petit bourgeois and small farmers ('Petit bourgeois'); (4) the skilled workers and routine occupations ('Routine occupations'); and (5) lower white-collar, which remains a class of its own. Although this reduces the variance in the poverty headcount to some extent, the most important differences remain. The countries in Figure 18.5 are ordered from left to right by the size of the difference between the highest and lowest poverty rates of each social class. The spread (i.e. the difference between the highest and lowest poverty rates of each social class) varies strongly across countries and is lowest in Czechia (8 p.p.) and highest in Romania (52 p.p.). It is important to note that, if the composite class of petit bourgeois and small farmers were disregarded, the ordering of countries would change quite substantially. However, even then in half of the countries the spread would be more than 10 p.p., reaching a high of 21 p.p. in Luxembourg (between salariat and routine occupations).

In nearly all countries, the salariat has the lowest AROP rate. The relatively low poverty risk applies to both the higher and lower salariat (with the exceptions of Austria, the Netherlands and Slovenia). Compared with the salariat, higher white- and blue-collar workers are confronted with similar or somewhat higher in-work poverty risks. More pronounced differences between the salariat and higher white- and blue-collar workers can be found in Lithuania, Portugal, Luxembourg, France, the United Kingdom, Estonia and Switzerland.

Figure 18.5: AROP rate by social class, population of working age in paid work, 60 % threshold, by country, 2018

(%)



Note: Countries are ordered by the absolute difference between the highest and lowest poverty rates. The value for 'Petit bourgeois' in Romania is 53 % and not displayed in Figure 18.5. Germany, Malta and Slovenia: based on first digit ISCO-08. Data for Slovakia are missing. The value for 'Petit bourgeois' in Denmark is not shown because of small sample size. 95 % confidence intervals are shown.

Reading note: In Romania about 13 % of the class of routine occupations are AROP in spite of being in paid work.

Source: Authors' computations, UDB March 2020.

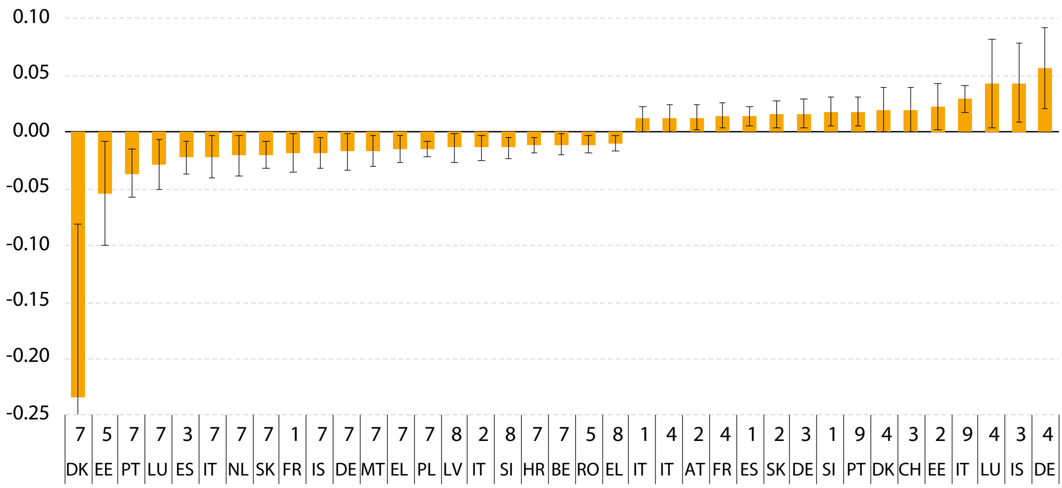
Also within this class there is a strong degree of internal homogeneity in poverty risks between higher blue-collar workers and higher white-collar workers (results not shown), with the exceptions of Greece, Italy, Norway, Slovenia and Sweden. Remarkably, in Sweden higher white-collar workers face as high a poverty risk as lower white-collar and those in routine occupations. Lower white-collar workers, skilled workers and those in routine occupations, generally face (much) higher poverty risks, but again with considerable variations across countries. In most countries where there is a substantial and significant difference between the two groups, skilled workers and those in routine occupations generally face higher poverty risks than lower white-collar workers. This is most apparent in Greece, Spain, Italy and Romania. With very few exceptions, poverty risks are highest among the petit bourgeois and, their poverty risk tends to be higher in countries where they account for a larger share of the population in paid employment. This is especially the case for Romania (53 % AROP) and Poland. In contrast to most other classes, heterogeneity within this class in terms of poverty risks is rather large, and especially so in Poland and Romania, where small farmers account for 8.7 % and 14.7 % of the population in paid employment respectively. In these two countries small farmers face by far the highest poverty risks, reaching about 40 % in Poland and a high of about 61 % in Romania ([198]).

18.4.3. The change from ISCO-88 to ISCO-08

When it comes to moving from ISCO-88 to ISCO-08, EU-SILC has set a very good example of how methodological changes could be handled, by providing both the old and the new variable for the same year. This offers a rare opportunity to estab-

([198]) Including production for own consumption does have a moderating effect on these very high poverty risks, reducing the poverty risk by less than 5 p.p. However, this does not make up for their very high AROP rates.

Figure 18.6: Difference in the AROP rate by social class between ESeC-08 and ESeC-88, nine–class structure, population of working age in paid work, 60 % threshold, by country, 2011 (p.p.)



Note: 1, higher salariat; 2, lower salariat; 3, higher white-collar; 4, petit bourgeois; 5, small farmers; 6, higher blue-collar; 7, lower white-collar; 8, skilled workers; 9, routine occupations. Horizontal axis shows country code and number of social class. Values ordered by the p.p. difference between the AROP rates of the same social class under ESeC-88 and ESeC-08. Only significant differences of at least 1 p.p. shown. 95 % confidence intervals shown.

Reading note: In Denmark the AROP rate of the lower white-collar class as measured by ESeC-08 is 23 p.p. lower than the AROP rate of the lower white-collar class as measured by ESeC-88.

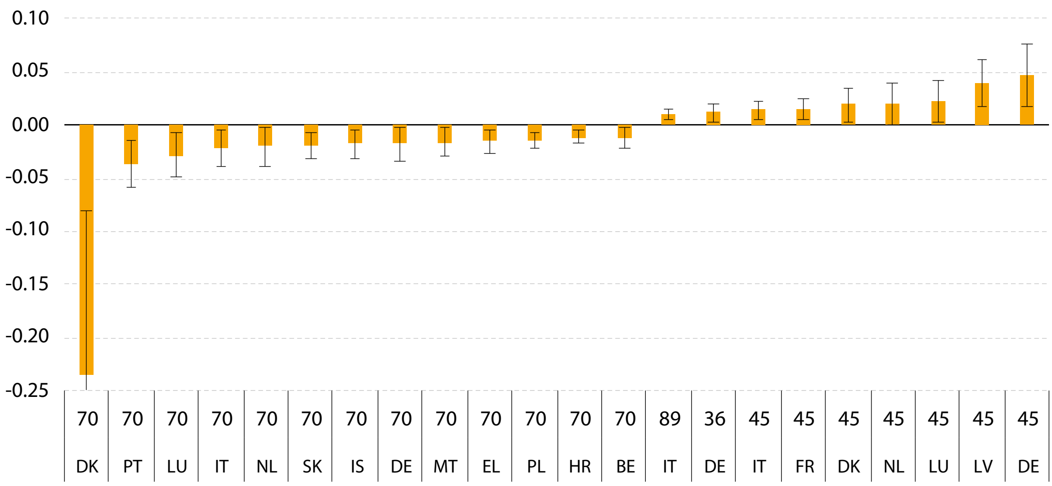
Source: Authors' computations, UDB March 2020.

lish with a high degree of certainty the impact this change has had. As highlighted above, the change to the new ISCO coding resulted in relatively substantial changes in the composition of individual and more aggregated social classes in many countries. Although the number of people who moved into and out of each class is important, Figures 18.6 to 18.8 show that, even for some classes with relatively minor changes in their share, the poverty risk was affected significantly (e.g. the class of small farmers in Estonia) ([199]).

When sticking to the nine-class structure, we find that, in 21 out of the 28 countries for which we have both codings available, the estimated poverty risk changed significantly (at 95 % confidence level) by at least 1 p.p. for at least one class. The number of substantially and significantly affected social classes is lower when applying a five- or three-class structure (in about 15 countries at least one class is substantially affected). The groups, and to some extent also the countries, affected depend to some extent on the level of detail of the class structure applied. In both the nine- and five-class structures, the change in ISCO coding has affected the poverty estimate for the lower white-collar class in particular, with a general reduction in the estimated poverty risk. Increases in estimated poverty risks affect the salariat, the higher white-collar workers, the petit bourgeois and routine occupations in a nine-class structure, but are remarkably concentrated among the petit bourgeois (including small farmers) in a five-class structure, and by extension in the 'middle class' in a three-class schema. At the same time, it must be said that, with few exceptions (most notably lower white-collar workers in Denmark), the impact on estimated poverty risks is rather moderate, especially when considering year-to-year fluctuations in the AROP rate of social classes (see below).

([199]) Please note that the requirement of having a statistically significant change rules out any substantial change in estimates that is not picked up owing to low sample sizes.

Figure 18.7: Difference in the AROP rate by social class between ESeC-08 and ESeC-88, five–class structure, population of working age in paid work, 60 % threshold, by country, 2011
(p.p.)



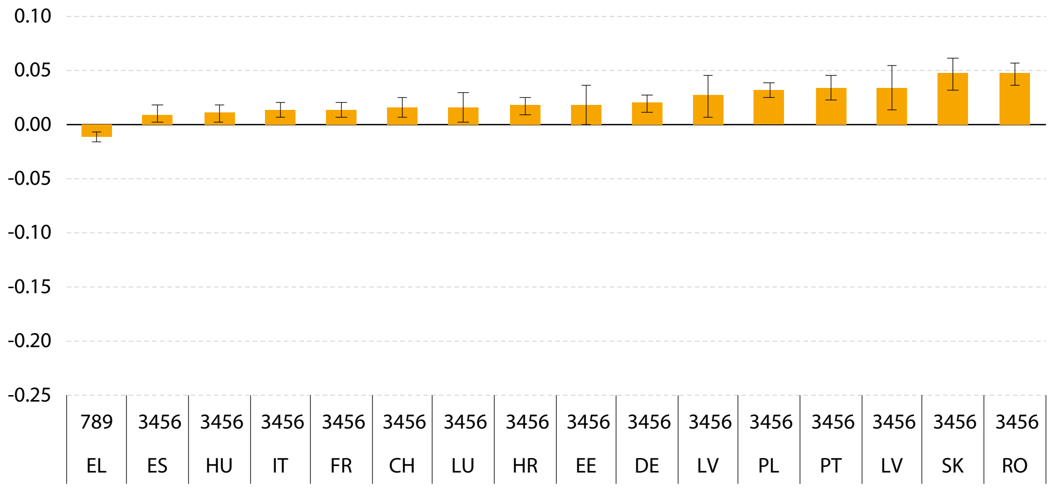
Note: 36, higher white- and blue-collar; 45, petit bourgeois; 70, lower white-collar; 89, routine occupations.

Horizontal axis shows country code and number of social class. Values ordered by the p.p. difference between the AROP rates of the same social class under ESeC-88 and ESeC-08. Only significant differences of at least 1 p.p. shown. 95 % confidence intervals shown.

Reading note: In Denmark the AROP rate of the lower white-collar class as measured by ESeC-08 is 23 p.p. lower than the AROP rate of the lower white-collar class as measured by ESeC-88.

Source: Authors' computations, UDB March 2020.

Figure 18.8: Difference in the AROP rate by social class between ESeC-08 and ESeC-88, three-class structure, population of working age in paid work, 60 % threshold, by country, 2011
(p.p.)



Note: 3456, higher white-collar and higher blue-collar workers, petit bourgeois and small farmers (i.e. the middle class); 789, lower white-collar, skilled workers and routine occupations.

Horizontal axis shows country code and number of social class. Values ordered by the p.p. difference between the AROP rates of the same social class under ESeC-88 and ESeC-08. Only significant differences of at least 1 p.p. shown. 95 % confidence intervals shown.

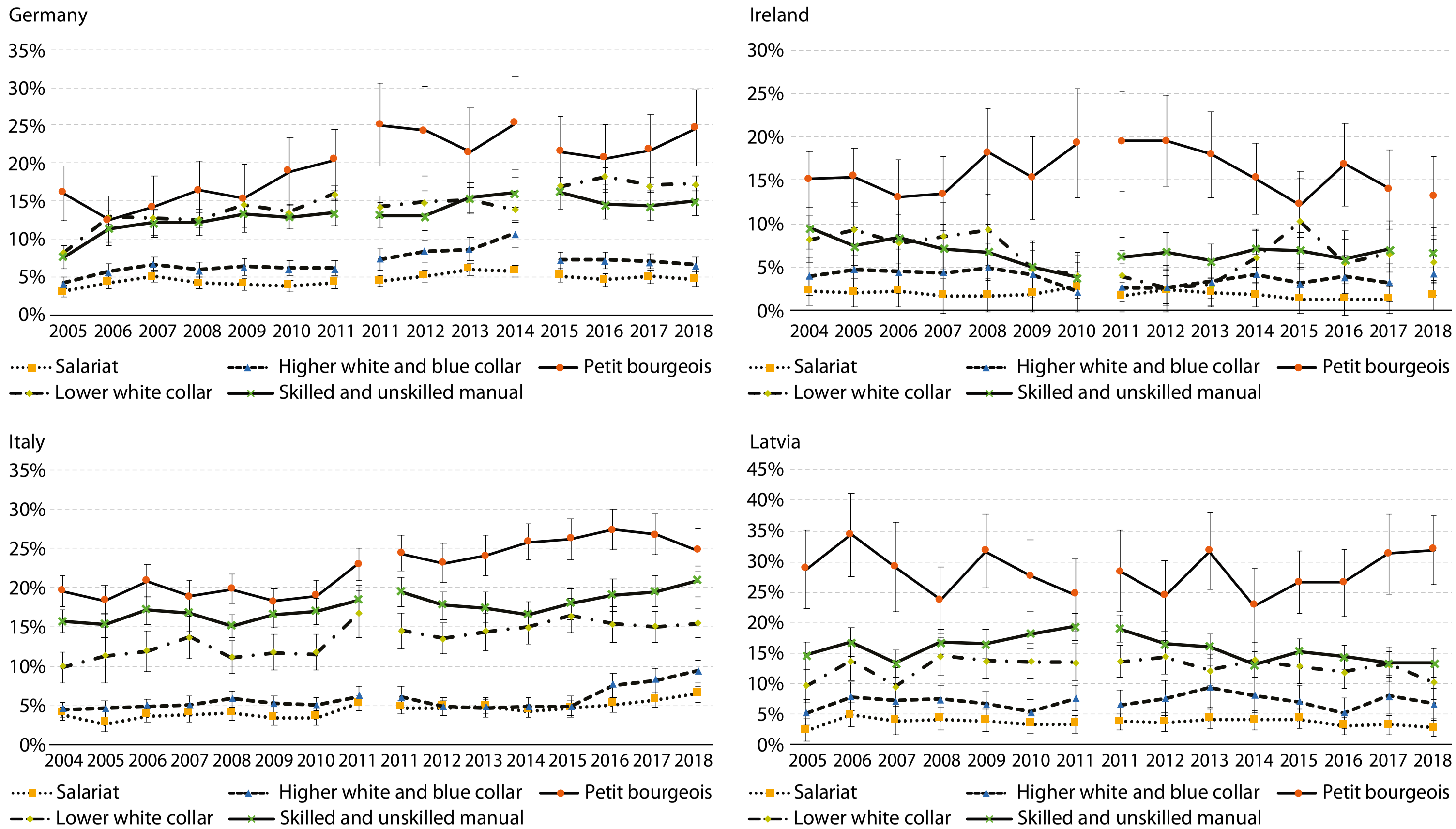
Reading note: In Romania the AROP rate of the middle class as measured by ESeC-08 is about 5 p.p. higher than the AROP rate of the middle class as measured by ESeC-88.

Source: Authors' computations, UDB March 2020.

18.4.4. Longer-term trends in selected countries

While the change from ISCO-88 to ISCO-08 is an obvious concern, other changes have also affected the quality and comparability of the derived social class variable in EU-SILC, most notably changes in the precision of the ISCO variable and availability of data about the self-employed. In this section, we illustrate the impact this may have had, taking four country cases – Germany, Ireland, Italy and Latvia – as examples, and put the 2011 break in broader perspective. Both Italy and Latvia displayed significant changes in the poverty risk of some classes (using the five-class structure) as a result of the move from ISCO-88 to ISCO-08. As Figure 18.9 shows, in Germany and Italy, ignoring the change in ISCO coding would lead to distorted conclusions regarding the size of some trends, whereas in Latvia, at least in the case of petit bourgeois and small farmers, this would add to the highly fluctuating pattern in poverty risks, with little effect on the poverty trend for other social classes. Similarly, moving to a different precision of the occupational variable seems to have had a more pronounced impact in Germany (move from 38 to 9 categories in SILC 2015) than in Ireland (move from 25 to 40 categories in SILC 2018), although we do not control for confounding factors that might explain these differences. It is noteworthy that the relatively large changes in the share and composition of some classes do not seem to have been translated into fundamentally different estimated poverty levels. Yet these four country cases also illustrate that caution is required when analysing social class in EU-SILC, especially when focusing on trends over time, and measurement issues should be kept in mind when interpreting results.

Figure 18.9: Trends in the AROP rate by social class, five-class structure, population of working age in paid work, 60 % threshold, 2004–2018
(%)



Note: Breaks in lines indicate breaks in series. When available, in the case of EU-SILC 2011 both ESeC-88 (before the break) and ESeC-08 (after the break) shown. 95 % confidence intervals shown.

Reading note: In Germany the estimated AROP rate of the petit bourgeois (including small farmers) went up from 16 to 25 %.

Source: Authors' computations, UDB March 2020.

18.5. Conclusion

Social class is a key variable for studying social stratification and the distribution of well-being. It has also been identified as an important determinant of varying levels of (in-work) poverty. While there are a number of studies that try to include social class in the analysis of EU-SILC, challenges to its operationalisation have received little attention. Therefore, in this chapter we have given an overview of some of the key challenges, and their impact on the comparability of constructed social class variables across time and countries. These challenges include in particular the (changing and varying) level of detail of the ISCO coding in EU-SILC and the move from ISCO-88 to ISCO-08 in 2011, as well as the varying degree of availability of key variables for the self-employed and the unemployed in particular, and, in countries with the single-respondent model, information on the non-selected respondents.

As this chapter shows, special care is required when analysing countries with less detailed and time-varying information on occupation, in particular Germany, Malta and Slovenia. Although researchers should be very careful about these caveats, we are convinced that they do not pose an insurmountable problem for informative comparative studies of social class with EU-SILC. This should encourage EU-SILC countries to continue collecting high-quality and consistent variables that allow the construction of a social class variable such as ESeC. Moreover, countries should consider collecting ISCO at three- or four-digit level and could discuss with the ESS how this can be done in the most efficient way. The current economic and health crisis also shows the added value of detailed information on occupation, and of using EU-SILC for timely estimates of its ongoing socioeconomic impacts (e.g. Palomino et al., 2020). Furthermore, we are strongly convinced that the decision to include in EU-SILC 2011 both the ISCO-88 and ISCO-08 variables is an example to be followed for other changes implemented in the data (and an example for other surveys). EU-SILC countries should consider applying a similar logic to country-specific changes. For instance, this would be extremely useful in the case of changes to the mode of data collection, especially when this concerns moving from survey to register data, or changes in the weighting scheme. Both of these changes are now implemented in Belgium, and the relevant 'old' and 'new' variables will be made available in the national SILC data set. These variables and similar ones for other countries could usefully be made available in the UDB released by Eurostat.

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19 Reconciliation of EU-SILC data with national accounts

Veli-Matti Törmälehto (200)

19.1. Introduction

National accounts (NA) include indicators and data that are useful for monitoring households' economic well-being, but there is a well-recognised need to complement aggregate indicators with distributional information derived from microstatistics (201). Recently, the OECD, Eurostat and the ECB have worked towards 'distributional NA', that is, distributional information fully consistent with household sector income, consumption and wealth aggregates (202).

Understanding and reconciling the differences between micro and macro sources is important even when the aim is not distributional NA as such. For instance, Nolan, Roser and Thewissen (2018) and Atkinson, Guio and Marlier (2017) examine the development of household incomes from both NA and micro perspectives. The latter also discuss the implications of micro/macro coherence of EU-SILC for social indicators such as AROP rates.

The motivation for this chapter is to address the following recommendation given by Atkinson, Guio and Marlier (2017, p. 77): 'Recommendation 3: The EU-SILC coverage of income by components exercise should be re-done, with a baseline appropriate for the calculation of social indicators.' They also suggest examining the sensitivity of conclusions to data deficiencies: 'the obvious question to ask is how far the AROP and other indicators are affected by proportionate adjustments to different income categories' (ibid.).

In this chapter, we experiment with sensitivity analyses of social indicators to microdata adjustments based on the gap between EU-SILC and reconciled NA estimates. The baseline is the EU-SILC income concept and social indicators. We start by discussing briefly the potential reasons for the differences in EU-SILC and macro estimates of total amounts. A key issue is different income concepts, and the chapter reviews and adjusts for the main conceptual differences between EU-SILC disposable income and NA gross household disposable income (GHDI). Finally, the EU-SILC data are modified with three different methods, at micro level, in order to examine the sensitivity of the income-based indicators to such adjustments.

We use the NSI version of the EU-SILC cross-sectional database (spring 2017 version) from income reference years 2010–2014. The income reference year is the calendar year prior to the survey year (2011–2015), except for Ireland and the United Kingdom. The national accounts data are from Eurostat, annual sector accounts, table nasa_10_nf_tr, retrieved in September 2017. We are not able to examine Germany, because the NSI data sets do not include German EU-SILC data. Moreover, we

(200) The author is at Statistics Finland. The author wishes to thank Sigita Grundiza, Anne-Catherine Guio, Tarja Hatakka, Tara Junes, Pierre Lamarche, Eric Marlier, Brian Nolan, Francesca Tartamella and Philippe Van Kerm for valuable comments and suggestions. All errors remain strictly the author's responsibility. This work was supported by Net-SILC3, funded by Eurostat and coordinated by LISER. The European Commission bears no responsibility for the analyses and conclusions, which are solely those of the author. Email address for correspondence: veli-matti.tormalehto@stat.fi

(201) For instance, the Social Protection Committee has adopted the growth rate in real unadjusted gross household disposable income ('unadjusted' here refers to the indicator not taking into account social transfers in kind) as the NA-based indicator; this indicator is now part of the EU portfolio of social indicators (Social Protection Committee, 2015).

(202) The OECD and Eurostat have focused on income and consumption, while the ECB concentrates on wealth in the expert group on distributional financial accounts.

are restricted to examining only countries that had separate and sufficiently complete S14 household sector accounts at the time of writing this chapter, which meant that we also had to exclude Ireland, Luxembourg, Malta, Austria and the United Kingdom.

19.2. Unadjusted coverage rates and potential reasons for the discrepancies

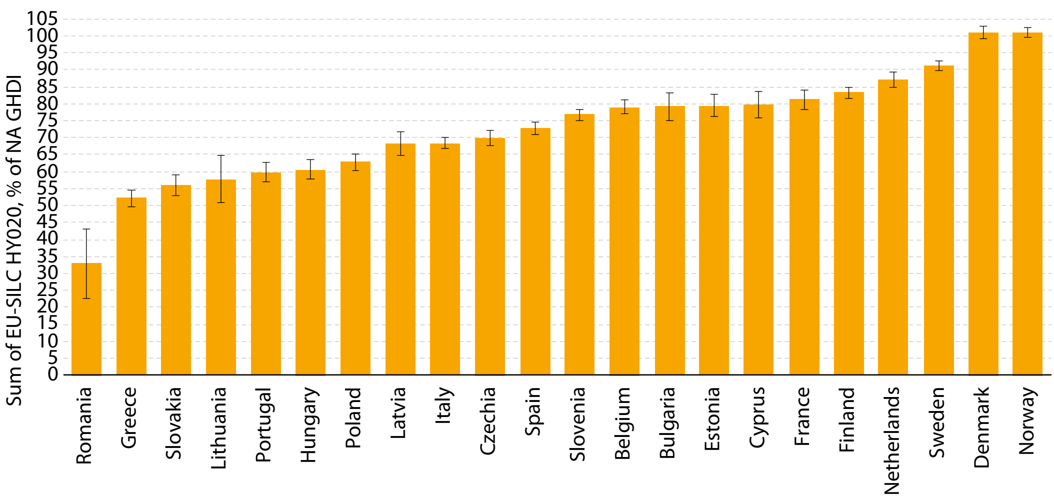
Neither NA aggregates nor survey estimates are error-free; they are both subject to their own measurement issues and biases. In spite of this, comparing surveys and NA is a common way to assess the accuracy of survey estimates. That comparison has to take into account differences in income concepts, population coverage and methods between the two sources. The importance of these varies across the countries. Nevertheless, the starting point is the coverage of the totals of disposable income before any modifications, shown in Figure 19.1. The coverage rates range from around one third to more than 100 %, and it is evident that sampling variance is not the root cause of the differences ([203]). The coverage levels and their variation are both worrying.

Aside from sampling variance, the gap could be due to generic reasons as well as various factors specific to surveys. The OECD Expert Group on Disparities in NA (Zwijnenburg et al, forthcoming) has identified several reasons for the observed gaps:

- population differences,
- conceptual and classification differences,
- measurement and estimation errors in microdata,
- quality of NA data,
- underground economy and illegal activities.

([203]) The estimated confidence limits are indicative only, as they do not take into account design features such as clustering, stratification, or calibration; in other words, they assume simple random sampling. Proper variance estimation is not feasible with the information available in the EU-SILC UDB, although this can be partially circumvented using pseudo-design information from Goedemé (2013).

Figure 19.1: Unadjusted coverage rates of EU-SILC disposable income to NA GHDI, income reference year 2014, EU-SILC survey year 2015
(sum of EU-SILC variable HY020, % of NA GHDI)



Reading note: In Romania, the estimated total sum of EU-SILC disposable income was 33 % (±10 %) of NA GHDI, before any modifications.
Sources: Author's computations, UDB 2015-1 (variable HY020) and annual sector accounts tables (transaction B6G S14).

The EU-SILC reference population excludes persons in collective households and institutions, such as prisons, hospitals, nursing homes or retirement homes, and persons who died or emigrated during the year. The incomes of these people are included in NA totals. The share of the population in non-private households ranged from 0.5 % to around 3 % in the 2011 census. This leads to the conclusion that differences in target populations are likely to have a minor impact on the coverage rates in the aggregate, although current transfers and property income may be affected more than the other income components (Törmälehto, 2019).

Regarding the quality of household data in the system of NA, the transactions in the household sector accounts are not compiled independently from the other sector accounts. Some bias may have to be allowed in the household sector to minimise bias and statistical discrepancies in the total economy. The data are derived from various data sources, such as tax administration and social security data, pension providers, business registers and other counterparts' data, and possibly by indirect methods. In the compilation process, the data sources are confronted (cross-checked), and the estimates are completed (balanced) in a coherent framework. By means of data confrontation and completion, the errors and inconsistencies of the primary sources can be corrected. Therefore, the NA estimates of household-sector aggregates should have less bias than any single-source statistic.

19.2.1. Conceptual differences

There are important conceptual and operational differences between the NA and EU-SILC operational income concepts, which need to be taken into account. Some transactions in NA do not exist in micro sources or are operationally different although conceptually related.

Given that our baseline is the EU-SILC income concept, the NA GHDI is adjusted in this chapter as follows to produce a more comparable aggregate benchmark:

- removal of gross operating surplus, non-life insurance, reinvested earnings on direct foreign investment, investment income on insurance policy holders, financial intermediation services indirectly measured (FISIM) part of interest received, net non-life insurance claims minus premiums, and miscellaneous current transfers;
- adding back interest paid before FISIM allocation (i.e. true interest paid), rents paid (land rents) and other current transfers paid.

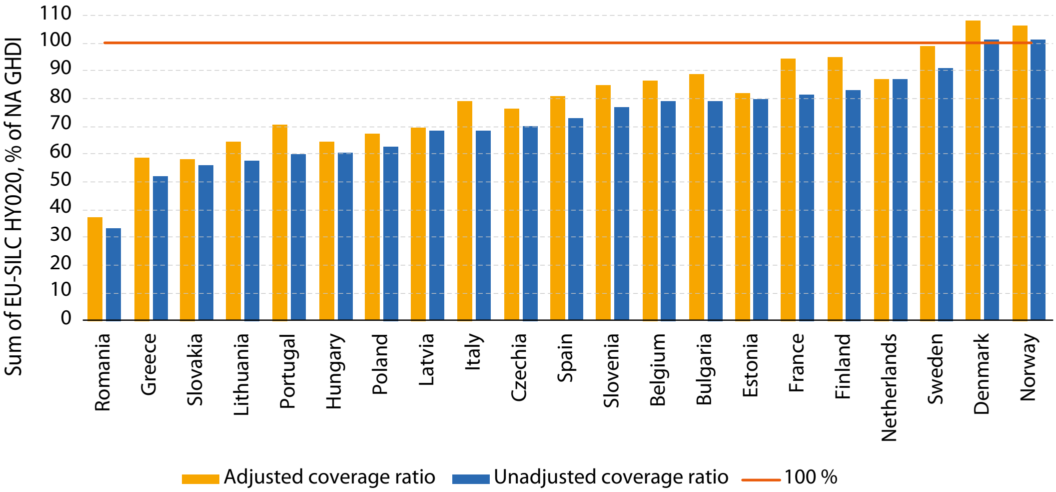
Further details on the conceptual adjustments and the comparisons are provided by Törmälehto (2019). Without access to national data, adjustments for the hidden economy and other specific adjustments are not possible.

The largest component in the adjustments in most countries is the gross operating surplus of households, which is conceptually the near equivalent of net imputed rents in EU-SILC. Net imputed rents are not included in the EU-SILC operational income concept [204]. The reconciled GHDI, after conceptual adjustments, is on average 90 % of the GHDI before adjustments, but ranges from 85 % in Portugal to 100 % in the Netherlands. The adjustments were relatively stable over 2003–2016 in most countries.

Figure 19.2 shows the ratio of EU-SILC disposable income to GHDI both after and before the adjustments. The adjustments improve the coverage rates, but there remain marked differences between the countries. In most countries, the adjusted coverage rates are still well below 100 %. In the Netherlands the subcomponents of adjustments cancel out in total, and in Denmark and Norway the adjusted coverage rates are well above 100 %.

[204] 'Net' in EU-SILC refers to imputed rents net of interest repayments on mortgage, but gross of deprecation (consumption of fixed capital). Net operating surplus in NA would refer to operating surplus net of consumption of fixed capital, but gross of interest repayments on mortgage. Net imputed rent would be available in the EU-SILC data for all countries, but it is excluded in this paper because it is not part of the current EU-SILC income definition used for calculating the EU social indicators.

Figure 19.2: Coverage rates of EU-SILC disposable income to NA gross disposable income, adjusted for conceptual differences, income reference year 2014, EU-SILC survey year 2015
(sum of EU-SILC variable HY020, % of adjusted/unadjusted NA GHDI)



Note: Only countries with sufficiently complete NA household sector data available are included.

Reading note: After adjusting for the main conceptual differences, the weighted sum of EU-SILC disposable income was 94.5 % in France in 2014. Without conceptual adjustments, the coverage ratio was 81.4 %.

Sources: Author's computations, UDB 2015-1 (variable HY020) and annual sector accounts tables (transaction B6G S14).

19.2.2. Quality of EU-SILC income totals

The comparability of EU-SILC income data across countries is a complex issue in itself (Zardo Trindade and Goedemé, 2020), let alone in comparison with an external source with its own mean squared error. The sole concern in national accounting is accurate estimation of the total amount of each transaction, without consideration of its distribution within an institutional sector. The task is more complicated in a sample survey, where the focus is on distributions. For any given income component *Y* observed for the responding sample, we can write the estimator of the population total income in a sample survey as:

$$Y = \sum W_i Y_i, = \sum(\pi_i \rho_i g_i) f(X, \varepsilon)_i, \qquad (19.1)$$

that is, as the sum of estimation weights W and measured incomes Y. The latter can contain measurement error and is also expressed as a function of the 'true' income X and an unknown error term ε. The estimation weights take into account different inclusion probabilities π_i, unit non-response and undercoverage adjustments ρ_i, and adjustment of weights to known population benchmarks g_i.

The formula in equation (19.1) encompasses challenges such as sampling and unit non-response bias, non-reporting and under-reporting, imputation bias and variance, and errors induced by net-to-gross conversion of incomes. All these are confounded in the estimated totals.

The crucial issue is what the properties of the measurement error term are, and if it is correlated with the 'true' incomes. Measurement errors of income in the EU-SILC context have been assessed by simultaneous measurement of income from interviews and registers (Nordberg et al., 2004; Statistics Austria, 2014; Méndez-Martin, 2015; Törmälehto et al., 2017) ([205]). Unfortunately, the empirical evidence on discrepancies between survey and register incomes seems somewhat country-specific and does not support a generic model of measurement errors applicable to many EU-SILC countries.

Aside from measurement, it should be noted that sampling designs matter and that the 'register countries' have more of their sample in the higher income groups (Törmälehto, 2019). This should improve the estimates, given that, on average, close to 40 % of total disposable income is concentrated in the top quintile in EU-SILC.

The coherence of NA and household survey data has been studied extensively in recent years (e.g. Fesseau et al., 2013; Eurostat, 2018). Törmälehto (2019) reports and discusses the coverage rates for the data used in this chapter and presented in the next sections. In particular, the ratio of EU-SILC wages and salaries to NA is less affected by conceptual differences than the other income components, such as self-employment income, and is a proxy of sorts for possible measurement issues.

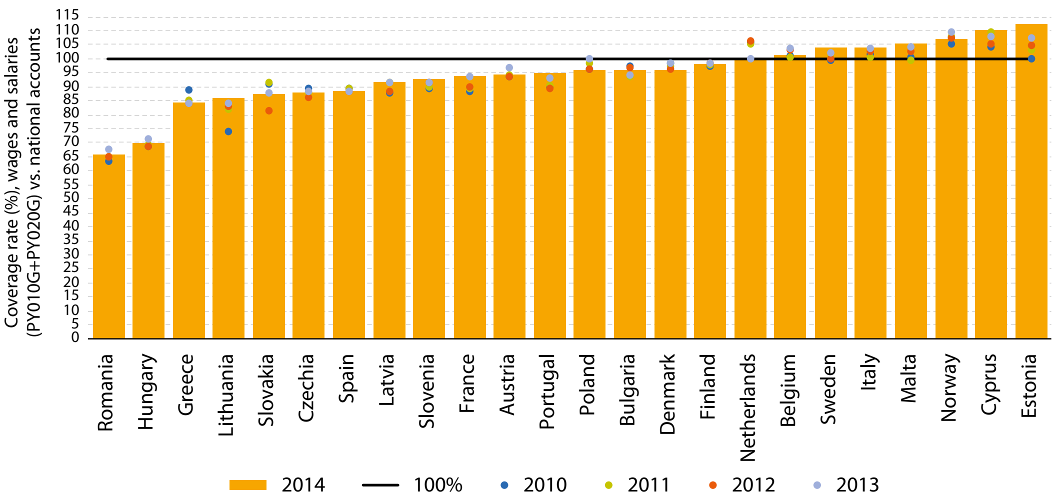
([205]) In Austria, the switch to mostly register data (on wages and salaries, and transfers) increased the total amount of disposable income only by 2.3 %. In Spain, the transition to a mixture of register and interview data increased the total amount by 14 %. The total amounts are based on the author's computations from two versions of the EU-SILC UDB 2011 before and after the transition. More in accordance with the Spanish data, the repeated measurement based on ECHP data in Finland from 1995 and 1999 suggested overall under-reporting of survey data by comparison with register data to be around 5–10 %, but with uneven patterns.

19.3. Coverage of wages/ salaries and transfers

As shown in Figure 19.3, the coverage rates of wages and salaries are generally high and stable, exceeding 90 % in many countries and with a median coverage rate of 95 % in 2014, but with substantial variation between the countries. The unadjusted coverage rates of disposable income seem to suggest that the use of administrative data in surveys improves coherence with NA, but in wages and salaries there is not a one-to-one relationship between data source and coverage rate.

Figure 19.3: Coverage rates of wages and salaries, income reference years 2010–2014, EU-SILC survey years 2011–2015

(% of wages and salaries in EU-SILC (PY010G + PY020G) versus NA)



Note: Only countries with sufficiently complete NA household-sector data available are included.

Reading note: In the Netherlands, the EU-SILC estimate of total wages and salaries was around 100 % of the NA total in 2013 and 2014, and around 105 % in 2010–2012 (PY010G + PY020G versus D11R).

Sources: Author's computations, UDB 2011–2015-1 and Eurostat, annual sector account tables (nasa_10_nf_tr).

As in the case of wages and salaries, the coverage rates for current transfers received were found to be relatively high in several countries, and consistently above 80 % in most countries (Törmälehto, 2019). The median of the country coverage rates is around 87 %. The median coverage rate of the taxes and social contributions is also high, close to 90 %, but there is more variation between the country coverage rates in taxes than in wages and salaries, although one would expect that properly measured coverage rates of taxes would correlate highly with those of wages and salaries.

Current transfers are likely to be received more by the institutionalised population, and thus the expected value of the coverage rate should be a couple of p.p. below 100 %. For instance, for Finland the in-scope population received 96.1 % of total current transfers measured in administrative registers, while the coverage rate with respect to NA was 93.3 % in 2014 (Törmälehto, 2019). We do not adjust for population differences in this chapter.

19.4. Coverage of self-employment and property income

In the following, we discuss in more detail only the coverage of self-employment and property income, given their importance for the subsequent microdata adjustments. As a rule of thumb, coverage rates higher than around 80 % (for wages and salaries, and transfers) or even 50 % (for property income) can be thought of as acceptable, considering measurement and estimation (representation) errors. Although the term 'property income' is used here, the comparison is essentially restricted to interest and dividends, and a more appropriate term could be 'capital income'.

19.4.1. Coverage of self-employment income

The coverage rates for self-employment income are much lower than wages and salaries or transfers, and exhibit high variation among the countries (Figure 19.4). The counterpart of EU-SILC self-employment income in NA is gross mixed income. It is usually derived using administrative records and/or business surveys and often includes large adjustments for unreported income (OECD, 2013).

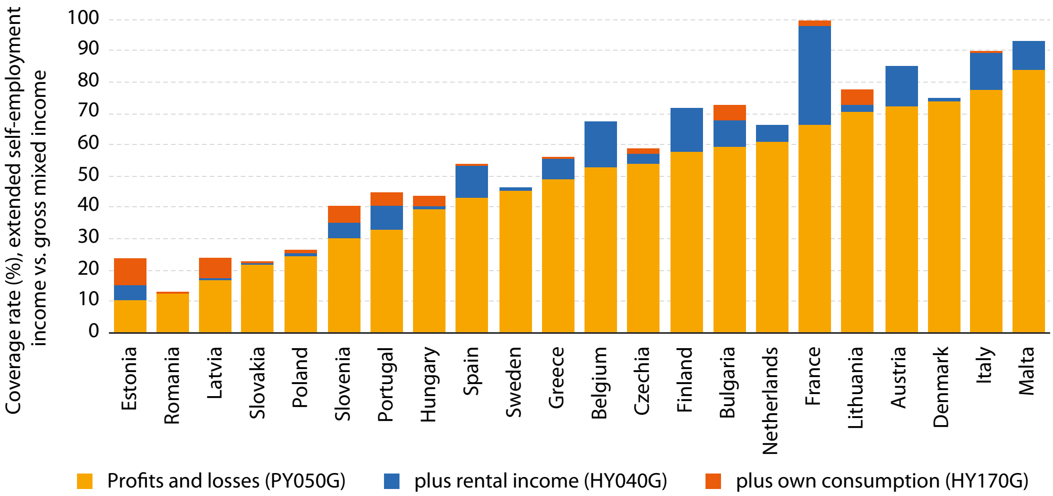
To be more comparable with mixed income, the EU-SILC concept of self-employment income needs to be modified by reclassifying rental income as self-employment income and by adding the value of goods produced for own consumption. The latter is not included in the EU-SILC income aggregates; however, conceptually it should be included when comparing the amounts with NA mixed income.

Extending EU-SILC self-employment income to cover the value of goods produced for own consumption (variable HY170G) and rental income (HY040G) results in adjusted coverage ratios that are higher than the comparison of profits and losses only (Figure 19.4). On average, the EU-SILC profits and losses variable (PY050G) covers around half of the NA gross mixed income, but with very wide variation between the countries. Adding own consumption and rents increases the coverage rates, significantly in some countries such as Estonia (because of own consumption) and France (because of rental income), but the rates generally are still low and remain below 90 % in all countries except Malta, Italy and France.

The method of data collection for self-employment incomes vary. The preferred method is to collect or ask for data on profit or loss based on accounting books or tax accounts, and, if these are not available, then ask about money drawn out of the business for non-business purposes. Some countries use administrative registers, essentially following business or tax account rules.

It is notable that the two countries with the highest coverage rates of profits and losses, Italy and Malta, use a combination of register and interview data for self-employment incomes. For instance, in Italy the income from self-employment is set equal to the higher of (1) the (net) self-employment income resulting from the tax report and (2) the (net) self-employment income reported by the interviewee. Although this has been adopted to improve comparability of Italian data, the Italian

Figure 19.4: Coverage rates of self-employment income and gross mixed income according to different definitions, income reference year 2014, EU-SILC survey year 2015
(%)



Note: Only countries with sufficiently complete NA household sector data available are included. Norway is excluded as an outlier owing to an apparent anomaly in NA data.

Reading note: In Estonia, the weighted total sum of profits and losses is 10 % of mixed income in NA. Adding rental income and own consumption would increase the coverage rate to 24 %.

Sources: Author's computations, UDB 2011–2015-1 and Eurostat, annual sector account tables (nasa_10_nf_tr).

coverage rates are very high compared with most other countries, including the register countries.

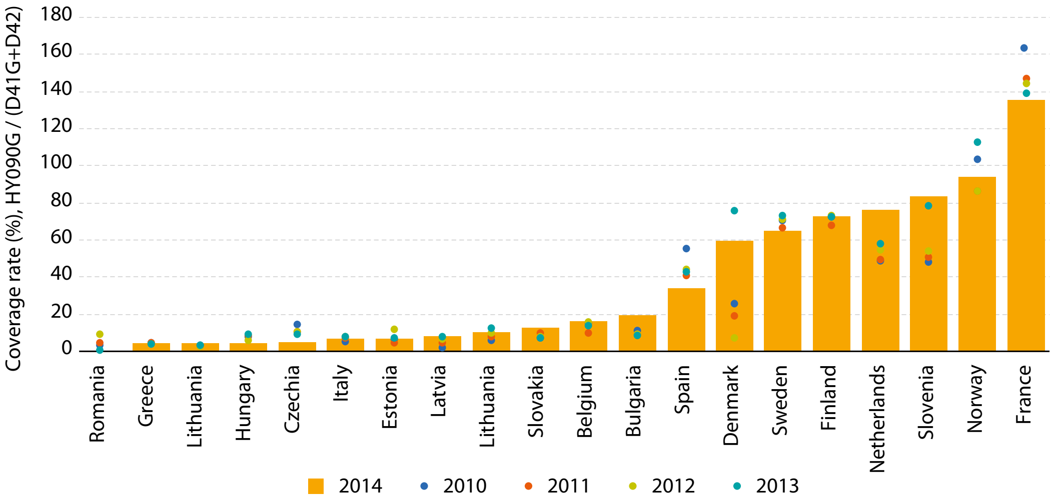
19.4.2. Coverage of interest, dividends and profit sharing

Coverage rates for property income received are generally found to be alarmingly low in sample surveys (see for example Eurostat, 2018). Even after significant adjustments for conceptual differences, essentially restricting the comparisons to interest and dividends, the level and variation in the EU-SILC coverage rates is quite striking (Figure 19.5). The adjusted coverage rates range from 1 % to 135 %. France is an anomaly, with the EU-SILC estimate far exceeding the NA value [206]. France combines register data, survey data and imputations to construct the target variable, which may contribute to this overestimation.

Aside from France, the coverage rates are above 50 % only in Denmark, Sweden, Finland, the Netherlands, Slovenia and Norway – all register countries. In Spain, which also uses register data, the coverage is better than in the rest of the countries. The coverage rates are very low, even below 10 %, in most survey countries and also in countries other than Spain that combine interview and register data (e.g. Estonia and Latvia).

([206]) For France, the macrodata include all components, actual and FISIM interest, dividends and withdrawals. The FISIM correction is small in France, and does not explain the difference. Withdrawals and dividends are roughly of equal size. Excluding withdrawals and using actual interest would increase the coverage rate even further.

Figure 19.5: Coverage rates of EU-SILC interest, dividends and profit sharing, income reference years 2010–2014, EU-SILC survey years 2011–2015
(% of actual interest received, dividends and withdrawals in NA – HY090G ÷ (D41G + D42))



Note: Only countries with sufficiently complete NA household-sector data available are included.
Reading note: In Slovenia, the weighted total sum of interest and dividends was 83.5 % of the NA aggregate in 2014, while it was 50 % in 2011.
Sources: Author's computations, UDB 2011–2015-1 and Eurostat, annual sector account tables (nasa_10_nf_tr).

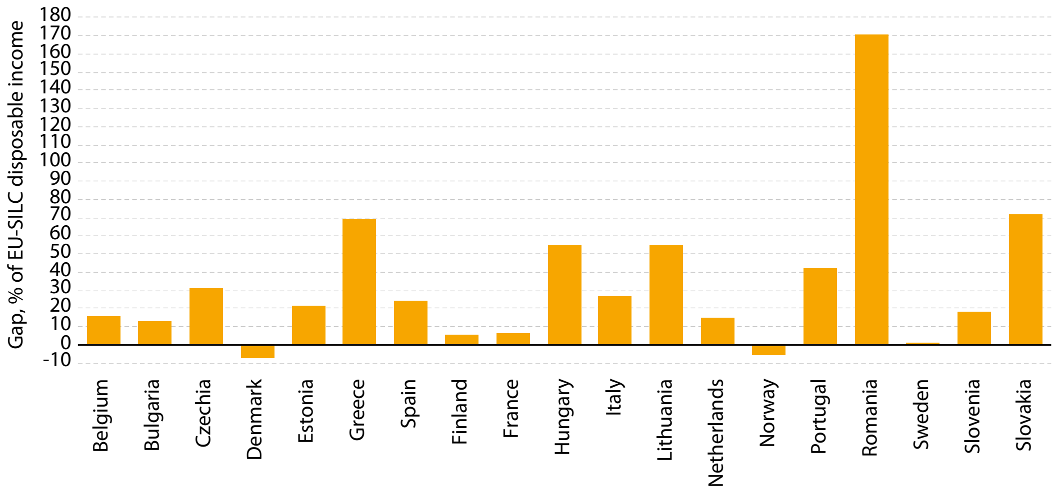
19.5. Adjusting EU-SILC survey data with national accounts data

The difference between the NA disposable income and the EU-SILC disposable income gap can be allocated to households in order to 'correct' the distributional estimates derived from a sample survey ([207]). The results of such exercises depend crucially on how well the gap can be assessed, and how it is allocated to households. The adjustment process needs to address the questions of 'how much' and 'to whom'. In this chapter, the gaps are based on modified NA aggregates and therefore interpreted as proxy measures for bias in the survey estimates. That is, the aim is not macroconsistency but adjustment of survey data to assumed data imperfections.

Figure 19.6 shows that the gaps ranged from negative to the extreme of 170 % of EU-SILC (Romania) totals in 2014. This is by how much, on average, we should increase the total disposable income in EU-SILC to be more coherent with a comparable macro-aggregate. Overall gaps are low in France and the Nordic countries. Note, however, that the gaps in the main components may offset each other in such a way that the overall gap appears small.

([207]) In the macroconsistent distributional NA context, the gaps would need to be allocated in full to households or household groups. Ideally the allocation should be done by making adjustments to the microdata. This would go towards a micro-founded household sector account, by building a macroconsistent microdata set by record linkage, imputations, statistical matching and other reconciliations (Coli and Tartamella, 2017).

Figure 19.6: Gap between EU-SILC and NA disposable income (after adjustments), income reference year 2014, EU-SILC survey year 2015
(% of EU-SILC disposable income)



Reading note: In Belgium, the NA GHDI was EUR 226.6 billion in 2014. After adjusting for the main conceptual differences, the NA total decreases to EUR 206.7 billion. The difference to EU-SILC total disposable income (EUR 179 billion) was EUR 27.6 billion, or 15.4 % of the EU-SILC total.

Sources: Author's computations, UDB 2015-1 and Eurostat, annual sector account tables (nasa_10_nf_tr).

19.5.1. Methods to adjust survey income data to external benchmarks

The allocation of the gaps to households ('to whom') is obviously a major challenge, and crucial for the distributional results. In our sensitivity analysis, we experimented with three adjustment methods and their combinations: (1) proportionate adjustments of income components, (2) adjustment of the survey weights by calibration to margins and (3) semi-parametric modelling (Pareto imputation).

In proportional scaling, individual values of income components are multiplied by the inverse of their coverage ratios. Consequently, the income compositions of households change, and therefore so does the overall income distribution. It is a very simple but feasible method and serves as the baseline adjustment in this chapter. The outcome of rescaling depends on the number of rescaled income components and their coverage ratios. In our experiment, wages and salaries, self-employment income and rents, interest and dividends, transfers received, and taxes paid were rescaled proportionally to the reconciled income concepts reviewed earlier ([208]).

Instead of adjusting the values of income, the reweighting approach adjusts the sampling weights as little as possible in such a way that the sum of income totals equals the external benchmarks. For technical reasons, reweighting had to be restricted to wages and salaries, and current transfers received. Reweighting also changes the demographic structure and the income components that are not adjusted. To account for demographic changes, the calibration constraints also include the original estimate of the household size distribution (in four categories), and the number of households and population size.

Instead of scaling the incomes of all recipients or changing the weights of all households, semi-parametric modelling can be used to explicitly allocate

([208]) In principle, gross incomes should be scaled up and taxes then recomputed based on these incomes. Proportional scaling of taxes had only a small impact on the results reported in this section.

the gap to a certain segment or segments of the distribution. In this method, the observed values in the right tail are replaced or modified with values drawn from a theoretical distribution, while retaining the survey values for the rest. A very common assumption is that the right tail of income distribution follows a Pareto distribution after a certain threshold (Atkinson, 2007; Jenkins, 2017).

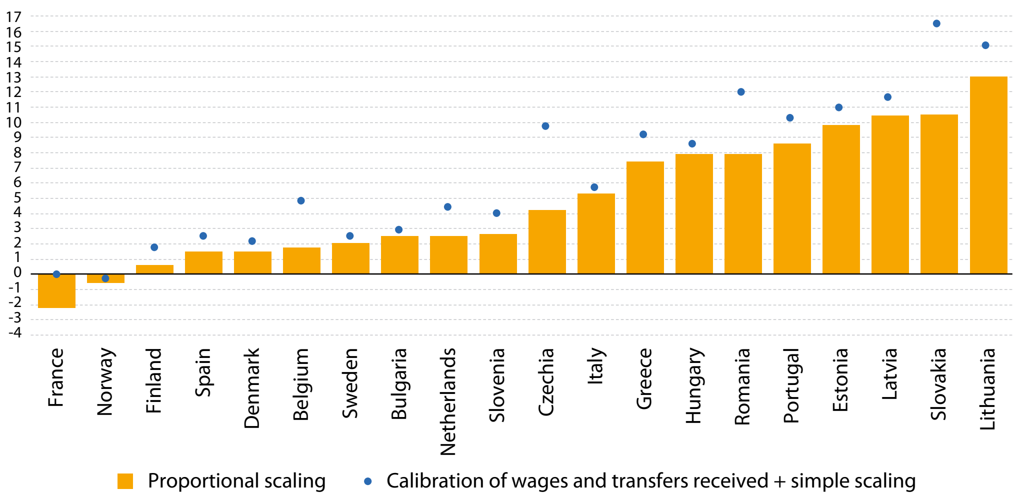
In this chapter, we create household-specific adjustment factors by drawing randomly from a Pareto distribution in such a way that the tail income total equals the measured values plus the gap to NA. The scale parameter of the Pareto distribution is not estimated but derived from the ratio of the conditional mean above the 95th percentile to the 95th percentile, after allocating the gap to the top 5 % (Törmälehto, 2019). This method avoids the need to estimate Pareto coefficients from complex sample data, which would be sensitive to the choice of an estimator applicable to survey data with sampling weights. The weakness of the method is the need to make an assumption about the allocation of the gap to the (unadjusted) income distribution. The results based on this method should therefore be considered only as a form of sensitivity analysis.

19.5.2. Results based on simple proportional scaling

Figure 19.7 shows the change in the Gini coefficient (expressed in %) after the adjustments based on proportional scaling. If we use a rule of thumb of 3 p.p. as a significant change, then in 10 countries the proportional scaling markedly changes the level of income inequality. Calibrating wages and transfers received while proportionally scaling the other components would result in somewhat larger increases than proportional scaling of all components, as shown by the dots in the graph.

The scaling factors for simple proportionate rescaling are reported by Törmälehto (2019), and are very large in a few countries, which leads to substantial

Figure 19.7: **Change in Gini coefficient after proportional scaling of main income components to modified NA aggregates, income reference year 2014, EU-SILC survey year 2015**
(p.p.)



Note: Calibration + simple scaling: wages and salaries, and current transfers are reweighted to match modified NA totals, and other income components are proportionally rescaled.

Reading note: In Italy, proportional scaling of the main income components would increase the Gini coefficient by 5.3 p.p. (from 32.4 to 37.7). The dot shows that the change would be 5.6 p.p. if wages and transfers received were calibrated and other components proportionally scaled.

Source: Author's computations, UDB 2015-1.

changes in the income distribution. The scaling factors are particularly large for property income and self-employment income, resulting in significant change in inequality and the income share of the top decile. The adjustments for regular income components, such as wages and salaries or pensions, are typically much smaller and apply to a larger number of households.

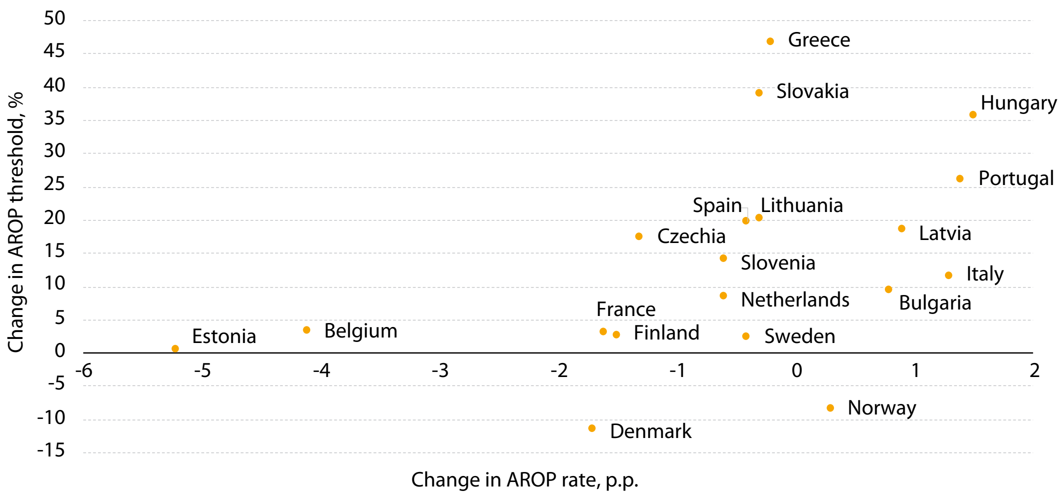
Figure 19.8 plots the changes in AROP rate and the threshold (i.e. median income) after the proportional scaling. The effect on AROP rates is more subdued than in the case of inequality, but median income level changes significantly in a few countries. The changes in the AROP rates are within ±2 p.p. in most countries. There are marked declines in Estonia and Belgium, however. The outcome is a result of the scaling factors, their relation, the income structures and the shape of the original distribution – a fairly complex process.

The median and therefore the AROP threshold increases significantly in several southern and eastern European countries, but very little in Belgium, France, Finland and Sweden. In Denmark and Norway, it decreases. Although large gaps and the method applied may result in very large increases in median incomes, AROP rates can remain almost unaffected (e.g. in Greece and Romania). On AROP rates, the calibration approach results in somewhat more modest changes than the proportional rescaling approach (Törmälehto, 2019).

19.5.3. Results based on semi-parametric modelling

In our Pareto imputation experiment, we combine self-employment income with interest and dividends, and modify the values above the 95th percentile to follow a Pareto distribution, in such a way that the total amount matches the NA to-

Figure 19.8: Change in AROP rate and threshold (60 % of median income) after simple proportional scaling of main income components to modified NA aggregates, income reference year 2014, EU-SILC survey year 2015
(% and p.p.)



Note: Romania is excluded as an outlier from the graph (increase in threshold by 135 %, AROP rate by 0.4 p.p.).

Reading note: In Italy, the AROP rate increased by 1.3 % and the AROP threshold by 11.5 % when the EU-SILC main income variables in the 2014 microdata were proportionally scaled up to corresponding NA totals.

Source: Author's computations, UDB 2015-1.

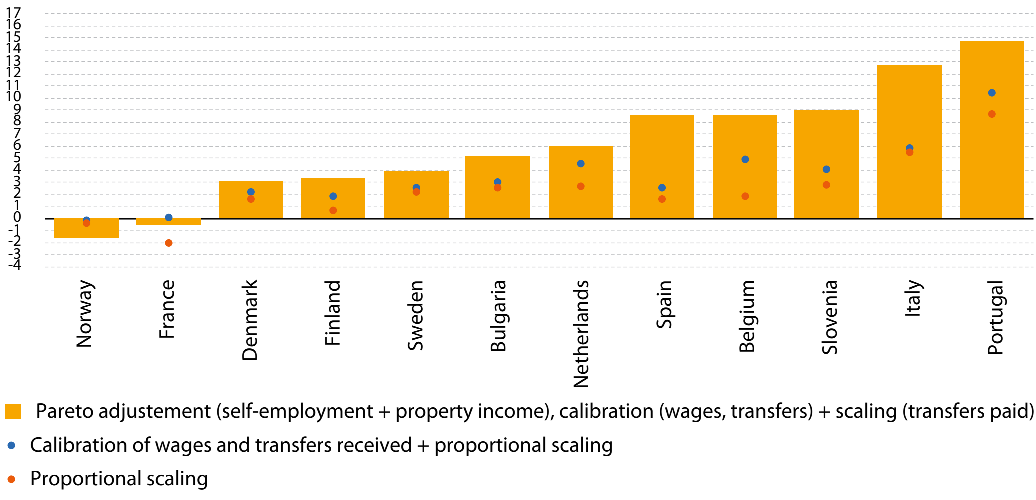
tal [209]. The Pareto assumption is more reasonable for these income components because their distribution tends to be much more skewed than wages or transfers received. They are combined because the number of households receiving interest and dividends is very low in some countries. For wages and salaries, and transfers received, we use the calibration approach, and for transfers paid the simple proportionate scaling.

After the adjustment, the assumption of Pareto distribution must hold when estimated from the sample survey data. To this end, we checked that the total sums conformed to the benchmarks, and that the empirical Pareto index (derived from the threshold and the conditional mean above the threshold) was close to the value of the theoretical distribution from which the samples were drawn.

Figure 19.9 shows the results for the countries for which the Pareto imputation could be conducted. For the countries not shown, the checks failed. These are countries mainly with small conditional sample sizes and large gaps in the sum of self-employment income and interest and dividends.

The results indicate that Pareto imputation approach increases inequality more than the other methods. This is expected, since the method is sensitive to the choice of the threshold and the size of the gap allocated to the top. In this experiment, the total gap was allocated to a small number of households at the top of the distribution (those above the 95th percentile), whereas in the other approaches the gap was distributed to the whole conditional distribution.

Figure 19.9: Change in Gini coefficient after Pareto replacement of top 5 % of self-employment income, and interest and dividends, income reference year 2014, EU-SILC survey year 2015
(p.p.)



Reading note: Bars show the results based on Pareto replacement of top 5 % of conditional distribution of self-employment income and dividends, calibration of wages and transfers, and simple rescaling of transfers paid. In Italy, these adjustments would increase the Gini index by 12.7 p.p. With the two other variants, the Gini index would increase around 5 to 6 p.p.

Source: Author's computations, UDB 2015-1.

(209) The threshold is set at the 95th percentile of the conditional distribution of the sum of self-employment income and interest, dividends and profit sharing. For all those above the threshold, the measured values of each household are adjusted so that the tail distribution conforms to a Pareto distribution. Note that the adjustment factor is household-specific, that is, the Pareto adjustment is done at micro level by changing the observed value of each household at the top of the distribution.

As expected, the Pareto adjustment of self-employment and property income instead of proportional scaling had a relatively small impact on the AROP rates. Overall, the results were quite similar to the hybrid approach (calibration of wages/salaries and transfers, rescaling of other components) and are not presented here (for more details, see Törmälehto, 2019).

19.6. Conclusions

The present chapter aimed to reconcile the main conceptual differences between EU-SILC and NA income aggregates, compared the estimated income totals by type between these sources based on these adjusted concepts, and finally applied different ways of adjusting the survey data to align with NA totals to assess the sensitivity of key inequality and AROP indicators. With regard to all these aims, the study revealed significant differences between countries, types of income and types of indicators.

The discrepancies between EU-SILC estimates of total amounts and NA totals prior to any adjustments can be very large and are not due to sampling variation. Differences in measurement and concepts are the most likely candidates to produce such large gaps and the between-country variation in them. Overall, the use of register income data improves coherence with NA, although there are certain unexplained differences in the subcomponents. The magnitude of the conceptual differences, such as for imputed rents and property income attributed to insurance policy holders, also varies between the countries. The necessary adjustments decrease the aggregate benchmark markedly more in some countries than in others.

The gaps for property income and self-employment income remain very large even after reconciliation of concepts, whereas the situation is satisfactory with wages and salaries, and transfers received. The assessment of the gaps is challenging and laborious, and depends on the quality of the NA data and the level of detail available in the cross-national databases. If the aim is to correct microdata with macrodata, it is essential to measure the micro/macro gap accurately so that it reflects the likely bias in the survey estimates rather than conceptual or methodological differences. A source of uncertainty in the adjustments comes from reliance on cross-national data in assessing the gaps. Proper assessment of the gap would benefit greatly from having access to detailed data available only in national sources. For instance, in the case of Finland the scaling factors for self-employment and property income derived from national data would be markedly lower than those derived from cross-national databases. With national data, the estimates of hidden self-employment income could also be either excluded or explicitly allocated to households.

The conceptual and measurement issues are particularly complex for self-employment and property income. Even if pooled together, the coverage rates for self-employment and property income remain low in many countries. More work is certainly needed on concepts and measurement of self-employment/mixed income and property income, including methods to impute or model property income based on asset values or external information.

Without knowledge of the distribution of the measurement error, the microdata adjustments are essentially arbitrary. We are in favour of more nuanced approaches applied at micro level. Any serious adjustments should be done with a microsimulation model and properly accounting for what is deemed to be correction of measurement error using macrodata and what is imputation to attain consistency with macro aggregates. Drawing distributional conclusions from macro-adjusted microdata should be accompanied with accessible sensitivity analysis and full transparency with regard to data sources and methods.

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20 Planned future developments of EU-SILC

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20.1. Introduction

The global financial and economic crisis of 2008 triggered several challenges for official statistics and, in particular, for social statistics. Currently, with the growing necessity to monitor and fight against the possible social consequences of the COVID-19 pandemic, social indicators are again playing a key role. Timely, reliable and comparable statistics are an indispensable tool for policymakers to describe the current situation and identify social patterns in order to take adequate, informed and effective policy measures. In this context, there is an increasing demand from stakeholders for new developments in EU-SILC to ensure the correct monitoring of the development of social exclusion phenomena, as it is the main data source for comparative analyses and indicators on income and living conditions in the EU.

At the same time, resources available to statistical authorities are under pressure in several Member States, and only coordinated efforts to achieve modern and cost-effective solutions are viable ways forward. Modernisation of social statistics is a key solution to meet the growing needs of users through improved statistical processes, reuse of data, and synergies achieved through integration and standardisation (see Section 20.3). The revision of EU-SILC is part of this process carried out by the ESS.

EU-SILC is a complex instrument involving different challenging methodological problems. The contribution of researchers is therefore a vital element for making EU-SILC a scientifically sound, effective and high-quality instrument. Hence, results from the methodological work on EU-SILC undertaken as part of various Net-SILC projects are being implemented in the process of producing EU-SILC data.

This chapter complements Chapter 2 of this volume, on the EU-SILC instrument, by describing the developments carried out in the modernisation of social statistics, especially regarding the revision and improvement made to EU-SILC, as well as the new legislation on its implementation that will come into force in 2021.

20.2. Policy context

With the launch in 2010 of the Europe 2020 strategy for smart, sustainable and inclusive growth, social indicators gained further relevance, making EU-SILC indicators an essential part of the group of the headline indicators, since inclusive growth is one of the three priorities of the strategy. A key objective of Europe 2020 was to lift 'at least 20 million people out of poverty or social exclusion' between 2010 and 2020 (see Chapter 1). As explained in Chapter 1, the AROPE indicator used for this target includes three components, which are computed on the basis of EU-SILC. In order to improve the measurement of deprivation, the new MSD indicator was adopted in 2017 by the indicators subgroup of the SPC, replacing the indicator adopted in 2009. The QJ indicator is also being revised, to adapt it to the current social and demographic situation in Europe.

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The continued monitoring by the SPC and the Commission, since 2001, of progress made towards the EU social protection and social inclusion objectives, and the analytical work carried out in the context of the European Semester have required the adoption of a large set of EU social indicators, which is constantly being updated, revised and enriched, and draws heavily on EU-SILC ([211]).

The European Pillar of Social Rights, which was proposed by the Commission and subsequently proclaimed, in 2017, by the European Parliament, the Council and the Commission, is supported by a social scoreboard to track trends and performances across EU countries ([212]). EU-SILC provides quantitative evidence to analyse the implementation of its social protection and inclusion key principles. The action plan for the implementation of the pillar, which the Commission proposed on 4 March 2021, is likely to increase the need for evidence.

Eurostat is monitoring at EU level the implementation of the UN 2030 agenda for sustainable development. In this context too, EU-SILC indicators are being used to monitor some of the SDGs, namely SDG 1, 'no poverty'; SDG 3, 'good health and well-being'; SDG 7, 'affordable and clean energy'; SDG 9, 'decent work and economic growth'; SDG 10, 'reduced inequalities'; and SDG 11, 'sustainable cities and communities' ([213]).

The necessity to monitor all these policies and measures has increased the demand for timely and reliable data on the social situation in Europe.

20.3. Modernisation of social statistics

The legal context of EU-SILC has changed. In September 2011, the ESSC adopted the Wiesbaden Memorandum on a 'New conceptual design for household and social statistics'. This memorandum calls for progress towards an overall common architecture for European social statistics together with actions on sampling frames, administrative data sources, measurement of the quality of life and of the living conditions of population subgroups, time use and household budgets. In September 2016, the ESSC adopted the Vienna Memorandum on 'Statistics on income, consumption and wealth'. This memorandum promotes, inter alia, the development of a harmonised income, consumption and wealth statistical framework, using a multisource approach and recommending closer cooperation with international organisations (especially the ECB and the OECD) and the research community, and closer cooperation between NA and sources of microeconomic data including household surveys on concepts related to income, consumption and wealth.

Regulation (EU) 2019/1700 of the European Parliament and of the Council establishing a common framework for European statistics related to persons and households, based on data at individual level collected from samples (the IESS regulation), was adopted in October 2019 ([214]). The underlying implementing acts pursuant to the IESS regulation were adopted in December 2019. They are:

- Commission Implementing Regulation (EU) 2019/2180 specifying the detailed arrangements and content for the quality reports;
- Commission Implementing Regulation (EU) 2019/2181 specifying technical characteristics as regards items common to several datasets;
- Commission Implementing Regulation (EU) 2019/2242 specifying the technical items of data sets, establishing the technical formats and specifying the detailed arrangements and content of the quality reports on the organisation of a sample survey in the income and living conditions domain.

The IESS regulation includes actions towards better integration of the data collection with standardisation of variables and modules, wider use of ad-

([211]) For more information on the EU social indicators, see the Directorate-General for Employment, Social Affairs and Inclusion web page (https://ec.europa.eu/social/main.jsp?catId=756).
([212]) For more information on the pillar, see the European Commission website (https://ec.europa.eu/commission/priorities/deeper-and-fairer-economic-and-monetary-union/european-pillar-social-rights/european-pillar-social-rights-20-principles_en).
([213]) See Eurostat's overview (https://ec.europa.eu/eurostat/web/sdi).
([214]) https://eur-lex.europa.eu/eli/reg/2019/1700/oj

ministrative data sources and improved statistical frames.

In line with these orientations and especially in accordance with the new regulation, Eurostat has worked on the modernisation of social statistics with the main objectives of increasing responsiveness to user needs, quality and efficiency. Concerning EU-SILC, the IESS regulation mainly requires the following:

- improve timeliness, with shorter deadlines for data submission;
- reformulate the precision requirements at national and regional (NUTS 2) levels for the AROPE indicator and the EU persistent AROP rate ([215]);
- add/change a number of variables;
- organise data collection according to three frequencies, namely 'nucleus', 3-year module and 6-year module;
- recommend prolongation of the longitudinal dimension, with at least a 4-year rotational scheme, and if possible a rotational scheme covering at least 6 years.

The new legislation enforces the need to improve EU-SILC data collection, processing, submission and reporting. This includes improvements in the sampling frames and data collection methods. In addition, NSIs are required to implement changes in common with other surveys under IESS. All these measures have been introduced in the revision of EU-SILC, which has come into force in 2021.

([215]) The persistent AROP rate is defined as the share of persons AROP in the current year and in at least 2 of the preceding 3 years.

20.4. Developments for EU-SILC

20.4.1. Purpose and motivation of the EU-SILC revision

The fight against poverty and social exclusion in the EU requires comparable statistics that are as timely as possible, to monitor this process. The demands for data on living conditions, income, inequalities and quality of life, and for (better) integration of these data with macroeconomics, are also increasing. Hence, the requests to improve EU-SILC are based on the following.

- Data timeliness, in particular in situations of economic and social crisis (when it is most necessary to closely monitor the social situation and the impacts of different policies) and for the European Semester.
- Regional data in the context of monitoring EU regional policy and, since 2020, for the allocation of funds, on the basis of indicators derived from EU-SILC, as well as the regional dimension of the Europe 2020 strategy.
- Poverty and social exclusion dynamics (including transitions and persistence).
- Multidimensional aspects of living conditions, poverty and social exclusion. Several requests could no longer be accommodated in the former mechanism of the ad hoc modules (e.g. more information on children, access to services, vulnerability, consumption and wealth, structure of households, quality of life and well-being, or health; more breakdowns of social benefits and transfers, social transfers in kind). More generally, the needs will continue to develop, and increased flexibility is required.
- Development of social indicators in the context of EU macroeconomic assessment (e.g. in the Macroeconomic Imbalance Procedure, which, so far, includes the AROPE indicator and its components only as auxiliary indicators) and more generally better integration of social and macroeconomic data.

- Increased use of administrative data for EU-SILC income components and the often associated problems of delays. New data collection modes and sources have been considered in the revision of the instrument (e.g. web interviews, matching).

As a consequence, the EU-SILC revision has been made in the framework of the IESS regulation and with the purpose of redesigning the instrument to:

- increase its responsiveness to new policy needs, currently and for the future;
- deliver data faster and provide information that is useful for early estimates;
- maintain the stability of the main indicators, with adapted frequency and keeping a cross-cutting approach allowing one to analyse different social phenomena in combination;
- allow analysis at regional level with sufficient precision;
- ensure adequate accuracy and quality of measurements;
- adapt to multimode and multisource data collections;
- allow better integration of its data with data coming from other ESS surveys;
- ensure general consistency of the different elements of the instrument (e.g. frequency of non-annual modules and length of the longitudinal component).

20.4.2. Proposed changes to assess the impact of the COVID-19 crisis on household living conditions

In the context of the COVID-19 pandemic, Eurostat has proposed various initiatives to investigate the impact of the current crisis on data collections and to measure its impacts on different social domains. Regarding EU-SILC, various recommended measures – which are still ongoing – have been proposed following consultations with countries.

- Temporarily change the data collection mode given the restrictions on conducting face-to-face interviews: move, where possible, to a non-contact mode of data collection (CATI or CAWI). If this is not possible, prolong the data collection period.
- In case telephone numbers of first-wave respondents are not known and a move from face-to-face interviews to telephone interviews is thus not straightforward, Eurostat has outlined several best practices that some countries have used to overcome the issue, such as sending letters by post to the first-year sample persons and asking them to contact statistical offices and provide phone numbers; oversampling the sample for the first wave of the survey; prolonging the fourth-year panel (or the last panel, if there are more than four) of the 2019 wave, in case the first wave households in 2020 are not reachable or the response rates are very low; investigate and use administrative sources to a larger extent; cooperate with other national institutions to obtain the telephone numbers of the respondents in the first wave of the panel.
- Collect information as it is at the time of the interview for variables related to the current reference period.
- Complement the regular quality reports for 2020 with additional information (if applicable), in particular on any changes of reference periods; completeness of the data set transmitted to Eurostat; sample size achieved; alterations to fieldwork period due to lockdown; changes implemented in mode of data collection; changes in data compilation; assessment of overall data quality; sampling and non-sampling errors; timeliness; and data comparability.
- The inclusion in the EU-SILC 2020 iteration of a set of voluntary variables on change in income since the previous year.
- The collection of an optional mini-module for the 2021 iteration to be able to evaluate the impact of the COVID-19 crisis on the households and to keep comparability in 2020 and 2021, including variables to measure the

changes in household income resulting from COVID-19. The proposed variables are related to changes in income, benefits, work and education.

20.4.3. EU-SILC revision

This section presents the main changes introduced in the revised EU-SILC that will be implemented from the 2021 iteration.

The modularisation of the content of EU-SILC and adaptation of the periodicity of collection of the modules will help to better satisfy increased analytical and monitoring needs. Until now, EU-SILC has collected annually about 135 non-technical variables from households or registers in the core questionnaire and about 20–25 in ad hoc modules. From 2021, the revised EU-SILC will include 'standardised' and 'core' variables, whose purpose is to meet the main objectives of the modernisation of social statistics. Standardised variables include a selection of key variables present in at least two EU social microdata collections. Core variables, a subset of these standardised variables, are included in all the social microdata collections. Introducing the changes that are required to harmonise the core variables within social surveys will lead to a break in the EU-SILC data series in 2021. The list of standardised variables (Table 20.1) is divided into three groups: 13 variables are priority 1 variables, meaning that they were harmonised at the first stage of the standardisation process, 14 variables are priority 2 variables and 11 variables are priority 3 variables.

Table 20.1: List of standardised variables

Priority	Variable	Core variable
1	(1) Sex	Yes
	(2) Age in completed years	Yes
	(3) Household grid	No
	(4) Partners living in the same household	Yes
	(5) Household size	Yes
	(6) Household type	Yes
	(7) Tenure status of the household	No
	(8) Main activity status (self-defined)	Yes
	(9) Full- or part-time main job (self-defined)	Yes
	(10) Permanency of main job	No
	(11) Educational attainment level	Yes
	(12) Participation in formal education and training (student or apprentice) in <reference period>	No
	(13) Level of the current / most recent formal education or training activity	No
2	(14) Country of birth	Yes
	(15) Country of main citizenship	Yes
	(16) Country of birth of the father	Yes
	(17) Country of birth of the mother	Yes
	(18) Country of residence	Yes
	(19) Duration of stay in the country of residence in completed years	No
	(20) Region of residence	Yes
	(21) Degree of urbanisation	Yes
	(22) Status in employment in the main job	Yes
	(23) Economic activity of the local unit for main job	Yes
	(24) Occupation in main job	Yes
	(25) Self-perceived general health	No
	(26) Long-standing health problem	No
	(27) Limitation in activities because of health problems	Yes

Priority	Variable	Core variable
3	(28) Net current monthly household income (*)	No
	(29) Existence of previous employment experience	No
	(30) Size of the local unit for main job	No
	(31) Supervisory responsibilities in main job	No
	(32) Year in which the person started working for current employer or as self-employed in main job (*)	No
	(33) Year when the highest level of education was successfully completed (*)	No
	(34) Field of the highest level of education successfully completed (*)	No
	(35) Interviewing mode used	No
	(36) Nature of participation in the survey	No
	(37) Stratum	No
	(38) Primary sampling unit	No

Note: (*) Not collected in EU-SILC.

Source: EU-SILC methodological guidelines for 2021 iteration.

The revised EU-SILC will collect yearly variables, the 'nucleus', which will cover income, key labour information, MSD and key variables on health, childcare, education, housing costs and quality of life. In addition, it will include rotating module variables, with a periodicity of 3 years for the variables dealing with labour, health, children and housing and a periodicity of 6 years for other topics, which change less over time (social participation, quality of life, access to services, wealth, debt, consumption, intergenerational transmission of disadvantages and possibly past experience of homelessness). Each module will contain about 20 variables. Some of the 6-year modules will be dedicated to new policy needs and will not be predetermined. In the first wave, respondents will also be asked about their characteristics that do not change over time (e.g. country of birth and education of parents, in the context of migration and intergenerational transmission). Table 20.2 provides a detailed description of the topics and module plans by year.

Table 20.2: Topic and detailed topics collected and module plans by years

Topic	Detailed topics	Periodicity	Years to be collected
Technical items	Data collection information	Yearly	2021–
	Identification	Yearly	2021–
	Weights	Yearly	2021–
	Interview characteristics	Yearly	2021–
	Localisation	Yearly	2021–
Person and household characteristics	Demography	Yearly	2021–
	Citizenship and migrant background	Yearly	2021–
	Household composition	Yearly	2021–
	Household composition – additional specific details	Yearly	2021–
	Duration of stay in the country	Yearly	2021–

Topic	Detailed topics	Periodicity	Years to be collected
Health: status and disability, access to, availability and use of healthcare and health determinants	Disability and Minimum European Health Module	Yearly	2021–
	Details on health status and disability	Every 3 years	2022, 2025, 2028
	Children's health	Every 3 years	2021, 2024, 2027
	Access to healthcare	Yearly	2021–
	Healthcare	Every 3 years	2022, 2025, 2028
	Access to healthcare (children)	Every 3 years	2021, 2024, 2027
	Health determinants	Every 3 years	2022, 2025, 2028
Labour market participation	Main activity status (self-defined)	Yearly	2021–
	Elementary job characteristics	Yearly	2021–
	Characteristics of the workplace	Every 3 years	2023, 2026
	Duration of contract	Yearly	2021–
	Employment status	Every 3 years	2023, 2026
	Detailed labour market situation	Yearly	2021–
	Supervisory responsibilities	Yearly	2021–
Job tenure, work biography and previous work experience	Previous work experience	Yearly	2021–
Working conditions including working hours and working time arrangements	Calendar of activities	Yearly	2021–
	Working hours	Yearly	2021–
Educational attainment and background	Educational attainment level	Yearly	2021–
	Educational attainment – details, including education interrupted or abandoned	Every 3 years	2023, 2026
Participation in education and training	Participation in formal education activities (current)	Yearly	2021–
Quality of life (QoL) including social, civil, economic and cultural participation, inclusion and well-being	QoL	Yearly	2021–
	Social and cultural participation	Every 6 years	2022, 2028
	Well-being	Every 6 years	2022, 2028
Living conditions, including MSD, housing, living environment and access to services	Material and social deprivation	Yearly	2021–
	Children-specific deprivation	Every 3 years	2021, 2024, 2027
	Main housing characteristics	Yearly	2021–
	Housing condition details, including deprivation and imputed rent	Every 3 years	2023, 2026
	Housing costs including reduced utility costs	Yearly	2021–
	Living environment	Every 3 years	2023, 2026
	Use of services, including care services and services for independent living	Every 6 years	2024
	Affordability of services	Every 6 years	2024
	Unmet needs and reasons	Every 6 years	2024
	Childcare	Yearly	2021–

Topic	Detailed topics	Periodicity	Years to be collected
Income, consumption and elements of wealth, including debts	Income from work	Yearly	2021–
	Income from social transfers	Yearly	2021–
	Income from pensions	Yearly	2021–
	Other incomes, including income from property and capital, and inter-household transfers	Yearly	2021–
	Taxes and contributions actually paid after reductions	Yearly	2021–
	Total annual income at household and respondent levels	Yearly	2021–
	Arrears	Yearly	2021–
	Overindebtedness, including reasons	Every 6 years	2026
	Elements of wealth, including dwelling ownership	Every 6 years	2026
	Elements of consumption	Every 6 years	2026
	Intergenerational transmission of advantages and disadvantages	Every 6 years	2023
	Housing difficulties (including renting difficulties) and reasons	Every 6 years	2023
	Assessment of own needs	Every 6 years	2026
Ad hoc subject	Living arrangements and conditions of children within separated or blended families		2021
Ad hoc subject	(to be defined at a later stage)		2023
Ad hoc subject	(to be defined at a later stage)		2025
Ad hoc subject	(to be defined at a later stage)		2027

Source: Annex 1 of Regulation (EU) 2019/1700.

The improvement of timeliness is another key objective of the modernisation of social statistics. The revised EU-SILC introduces changes in the data submission deadlines that will be implemented with effect from the 2021 data collection. The new EU-SILC will include two different types of data transmission from national statistics offices to Eurostat: transmission of 'regular' data and transmission of 'provisional' data. The deadlines will be as follows:

- regular data:
  - by the end of year N, submission of cross-sectional and longitudinal target variables for the data collection of year N, including cross-sectional weights;
  - in exceptional cases, microdata concerning income variables may be submitted as provisional data;
  - by 28 February of year N + 1, receipt of revised, final income data;
  - by end October of year N + 1, at the latest, submission of longitudinal weights to complete the data files;
- provisional data:
  - by end of year N, provisional data (on income only) can be submitted; countries are invited to inform Eurostat in September of year N whether the data files of year N will include provisional data or not.

This new schedule will improve the overall availability of EU-SILC data by at least 6 months. It will

Figure 20.1: 6-year rotational model

	Time 1	2	3	4	5	6
Panel 1	**Wave 6**					
Panel 2	**Wave 5**	**Wave 6**				
Panel 3	**Wave 4**	**Wave 5**	**Wave 6**			
Panel 4	**Wave 3**	**Wave 4**	**Wave 5**	**Wave 6**		
Panel 5	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**	**Wave 6**	
Panel 6	**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**	**Wave 6**
Panel 7		**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**
Panel 8			**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**
Panel 9				**Wave 1**	**Wave 2**	**Wave 3**
Panel 10					**Wave 1**	**Wave 2**
Panel 11						**Wave 1**

make income data available at the end of survey year N or at the beginning of N + 1. In addition, it will introduce elements in the collection that will be useful to estimate developments in income distribution.

Users are highly interested in analysing trajectories into and out of poverty. Consequently, as has been explained above, the rotational panel will be extended, where possible, from 4 to 6 years, to have better estimates of longer phenomena (the persistent AROP indicator will then be based on a sample size double what is currently feasible) and to improve the study of transitions and recurrences of poverty and social exclusion. The proposed rotational scheme is shown in Figure 20.1.

The regional dimension of EU-SILC is becoming increasingly important. The IESS regulation states that reliable statistics should be provided at national and regional (NUTS 2) levels. In the longer term, efforts should be made to achieve more detailed local data, based on the infrastructure set up under Directive 2007/2/EC of the European Parliament and of the Council ([216]). To allow for more regional breakdowns, on a country-based approach, a combination of several solutions will be used by Member States, including redesign of the sample, modelling and calibration, and in some cases increased sample size.

As stated in Section 20.3), one of the objectives of the IESS regulation is to reformulate the precision requirements at national and regional (NUTS 2) levels for the AROPE indicator and the persistent AROP rate. In IESS, these requirements are expressed in standard errors and are defined as continuous functions of the actual estimates and of the size of the statistical population in a country or in a NUTS 2 region.

The estimated standard error of a particular estimate $\widehat{SE}(\hat{p})$ must not be higher than:

$$\sqrt{\frac{\hat{p}(1-\hat{p})}{f(N)}}$$

The function *f(N)* has the following form: $f(N) = a\sqrt{N} + b$.

The values used for parameters N, a and b are provided in Table 20.3.

([216]) Directive 2007/2/EC of the European Parliament and of the Council of 14 March 2007 establishing an Infrastructure for Spatial Information in the European Community (INSPIRE) (OJ L 108, 25.4.2007, p. 1).

Table 20.3: Parameters used for AROP

$\hat{p}$	N	a	b
Ratio of people AROPE to population	Number of private households in the country in millions and rounded to three decimal places	900	2 600
Ratio of people at persistent risk of poverty to population	Number of private households in the country in millions and rounded to three decimal places	350	1 000
Ratio of people AROPE to population in each NUTS 2 region	Number of private households in the NUTS 2 region in millions and rounded to three decimal places	600	0

Source: Annex II of Regulation (EU) 2019/1700.

As regards the estimated ratio of people at risk of poverty or social exclusion to the population in each NUTS 2 region, these requirements are not compulsory for NUTS 2 regions with fewer than 0.500 million inhabitants, provided that the corresponding NUTS 1 region meets this requirement. NUTS 1 regions with under 100 000 inhabitants are exempted from the requirement.

Another notable change in the revised EU-SILC is the introduction of information on the interview mode within the standardised variables. This will collect the interview mode used for the household questionnaire, comprising the categories PAPI, CAPI, CATI, CAWI and 'other'. In addition, it will be possible to combine different interviewing modes (i.e. mixed-mode interview). In such cases, the interviewing mode predominantly used will have to be reported. Specific rules concerning quality reporting will have to be provided for each microdata collection.

Some tracing rules will change with the new EU-SILC. The first change relates to the age of the sample persons. The group of follow-up persons will be modified from those aged 14 or over at the time of selection of the initial sample for a panel to persons aged 16 or over at the end of the income reference period at the time of selection. In addition, people who have moved out of the household to another place of residence for 12 months or more will no longer be considered members of their previous household. Lastly, information collected on former residents (the 'former household members') and sample persons who have died will be reduced.

Finally, the revised EU-SILC also introduces other improvements such as modifications in the quality reports. The national quality reports for EU-SILC will have to be delivered 3 months after the data transmission deadline specified in the IESS regulation. They will have to follow the ESS standard for quality reports structure, which covers 12 topics, and will also include some additional subtopics specific to EU-SILC.

20.5. Conclusions

The need for high-quality and timely comparative social indicators has grown exponentially at EU level since the first EU poverty and social exclusion indicators were adopted in 2001 by EU Heads of State and Government (the Laeken indicators). The social context and the economic situation of Europe make EU-SILC a key data source for comparative analysis on income and living conditions, which has to adapt to the new policy demands.

The IESS regulation is an important step in the modernisation of social statistics, which will contribute to creating a common framework for European statistics relating to persons and households. The revised EU-SILC will be fully implemented from the 2021 iteration, requiring a challenging process at legal and technical levels. However, both Eurostat and the NSIs in the EU Member States and neighbour countries have already started implementing a number of changes in the current EU-SILC, in particular changes related to timeliness and regionalisation.

In view of the complexity of EU-SILC and the challenges of its modernisation, it is essential to ensure that researchers participate in the process and, more generally, in the improvement of the instrument. In this regard, contributions from Net-SILC are important examples of fruitful collaboration between the ESS and the research community.

Appendix 1: Composition of Net-SILC3

Net-SILC3 brings together expertise from ESS bodies and academics. It consists of the following partners:

- ESS bodies:
  - the coordinator (LISER),
  - Statistics Austria, Statistics Finland, Statistics Latvia, Statistics Luxembourg, Statistics Netherlands, Statistics UK,
  - Sciensano (Belgium),
  - Bank of Italy (associated partner);
- academic/research bodies:
  - Institute for Social and Economic Research of the University of Essex, United Kingdom,
  - Herman Deleeck Centre for Social policy, University of Antwerp, Belgium,
  - Oxford University, United Kingdom,
  - Stockholm University,
  - University of Manchester, United Kingdom,
  - University of Amsterdam, Netherlands.

Appendix 2: Abbreviations

Official Member State abbreviations	
AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czechia
DE	Germany
DK	Denmark
EE	Estonia
EL	Greece
ES	Spain
FI	Finland
FR	France
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxembourg
LV	Latvia
MT	Malta
NL	Netherlands
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia

Other (non-EU) EU-SILC countries covered in some chapters	
CH	Switzerland
IS	Iceland
NO	Norway
RS	Serbia
UK	United Kingdom

Other abbreviations	
AAA	average annual approximation
ACS	American Community Survey
AROP	at risk of poverty
AROPE	at risk of poverty or social exclusion
CAPI	computer-assisted personal interview
CATI	computer-assisted telephone interview
CAWI	computer-assisted web Interview
CE	conditional effect
COVID-19	coronavirus disease 2019
Degurba	degree of urbanisation
EAA	euro area average
ECB	European Central Bank
ECHP	European Community Household Panel
EFTA	European Free Trade Association
ELSTAT	Hellenic Statistical Authority
ESeC	European Socio-economic Classification
ESIF	European Structural and Investment Funds
ESS	European Social Survey
ESSC	European Statistical System Committee
ESSPROS	European system of integrated social protection statistics
EU	European Union
Eurostat	Statistical Office of the European Union
EU-SILC	European Union Statistics on Income and Living Conditions
FGT	Foster–Greer–Thorbecke
FISIM	financial intermediation services indirectly measured
GDP	gross domestic product
GESIS	Gesellschaft Sozialwissenschaftlicher Infrastruktureinrichtungen
GHDI	gross household disposable income

IESS	integrated European social statistics
IF	influence function
IQ	insufficient quality
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
ISER	Institute for Social and Economic Research
ISTAT	Italian National Statistical Institute
LB	left behind
LISER	Luxembourg Institute of Socio-Economic Research
LNOB	leaving no one behind
MPI	multidimensional poverty indicator
MPI1	first multidimensional poverty indicator
MPI2	extended multidimensional poverty indicator
MSD	material and social deprivation
n.a.	not available
NA	national accounts
Net-SILC	Network for the Analysis of EU-SILC
Net-SILC3	third Network for the Analysis of EU-SILC
NSI	national statistical institute
NUTS	Nomenclature of Territorial Units for Statistics
OECD	Organisation for Economic Co-operation and Development
OPHI	Oxford Poverty and Human Development Initiative
PAPI	paper and pencil interview
p.p.	percentage points
PPP	purchasing power parity
PPS	purchasing power standards
PSU	primary sampling unit
QJ	(quasi-)joblessness
RQR	regional quintile ratio
S14	household sector in the national accounts
SDG	Sustainable Development Goal
SIC	social insurance contributions
SMD	severe material deprivation
SPC	Social Protection Committee
UDB	User Database
UE	unconditional effect
UN	United Nations

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Improving the understanding of poverty and social exclusion in Europe

EDITED BY ANNE-CATHERINE GUIO, ERIC MARLIER AND BRIAN NOLAN

Using the data from the `European Union Statistics on Income and Living Conditions' (EU-SILC), this book reflects the results of almost 5 years of research involving data producers and data users. It aims to improve our understanding of substantive challenges facing `Social Europe' and to contribute to the development of methods that provide new insights into the determinants and dynamics of income and living conditions. Through in-depth analyses, it enhances our knowledge of a wide range of topics: inequalities, role of social transfers, mortality risk due to poverty and social exclusion, intra-household variation in deprivation, between-country differences in housing conditions, unmet medical need, child deprivation, migrants' living conditions, as well as the dynamics of in-work monetary poverty and deprivation and of multidimensional poverty. The book also puts forward robust policy-relevant indicators in these fields, including longitudinal indicators. This volume is intended both for policy-makers and statisticians and for all those concerned about the impact of economic and social policies on people's lives and the ways in which the social dimension of Europe and its monitoring can be reinforced.

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